CS6811 – Project Work

First Review

UAV-based post-disaster 3D scene reconstruction for efficient survivor detection

Team Number: 17 (Batch 1)

<u>Project Guide:</u> Dr. R. Gunasekaran

Team Members:

Abhishek Manoharan Nishanthini S Vamsi Raju M 2019503502 2019503537 2019503568

<u>Domains:</u> Unmanned Aerial Vehicles, Computer Vision, 3D Reconstruction

Problem Definition:

Post-disaster scene understanding frameworks are becoming increasingly crucial in search and rescue operations and damage assessment initiatives. The use of Unmanned Aerial Vehicles (UAVs) provides an efficient method to complete the task of scene understanding. However, complex environments present in post-disaster scenarios make it difficult for UAVs to detect humans or objects accurately. Moreover, inefficient object detection mechanisms lead to low accuracy and a long time for object detection tasks. Hence, to mitigate these issues, we propose a UAV-based scene understanding scheme involving a GANaided 3D reconstruction mechanism. This approach deploys a Generative Adversarial Network (GAN)-based model to denoise and remove occlusion in the images obtained from the UAVs. The framework classifies objects present in the visual scope of the UAV using a 3D reconstruction of the images obtained from the UAV, followed by semantic segmentation, resulting in pixel-level prediction and classification of entities present in the 3D model. Furthermore, an ensemble network consisting of a combination of single-stage and multi-stage detectors is to be used to improve the performance of the survivor detection model. This will help reduce the false negative rate and improve the overall accuracy of the system.

Literature Survey:

S.No	Publication	Title	Proposed Work	Limitations
	Venue and Year			
1.		UAV-Based Real-Time Survivor Detection	 ❖ This paper proposes a new thermal image dataset consisting of 6447 thermal images designed for survivor detection using UAVs in post-disaster scenarios. ❖ The paper also describes optimal values to prune survivor detection models in order to reduce the complexity of the models. ❖ The model applies knowledge distillation techniques to fine-tune them and improve accuracy. ❖ The performance of several survivor detection models based on YOLOv3 and 	Older and inferior detection models have been used for survivor
			YOLOv3-MobileNetV1 were compared with and without pruning and fine-tuning.	
2.	IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-16 (2022)	Swarm UAV SAR for 3-D Imaging	 This paper implements a 3D imaging mechanism for 2D images obtained from a swarm of UAVs. The proposed work involves the 3D imaging of a scene by the usage of 2D images obtained from several UAVs 	considerable amount of data must be transmitted from the UAV swarm, as images obtained from each node in

					1	.1
			Sw pe po Th ob tri Bu us	rarm at d rspectives wit ints of overlar	cloud then and nent is the 3D	the swarm are used to produce the 3D rendering. Multiple UAVs also need to exchange information in order to efficiently collect data of the scenario.
3.	IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 11, pp. 8879-8889 (2019)	Method for 3-D Scene Reconstruction Using Fused LiDAR and Imagery From a Texel Camera	ground de	atively low-a vigation syste	study bundle chnique mages. enables ccuracy ems to with	Outliers present in the point cloud are not identified and mitigated, thereby leading to lower accuracy.
4.	25th IEEE International Conference on Pattern Recognition (ICPR), pp. 10227-10234 (2021)	SyNet: An ensemble network for object detection in UAV images	❖ W low new state im the au property in the state im the state important.	th the go wering the hig gative rate o age detector proving the qu	f multi- rs and uality of le-stage sals, the esearch nsemble SyNet a multi- with a	According to the investigation, detecting objects in drone images is more challenging than detecting them in images that were taken from the ground, even with the most

		1		a al
				advanced
				object
				detection
				algorithms.
				❖ Hence, the
				accuracy of
				the model
				trained on
				UAV images is
				still low
				compared to
				models
				trained on
				ground
				images.
5.	IEEE	Vehicle	The article provides a	Videos captured
	Transactions on	Detection	review of vehicle	in the UAVs are
	Neural	From UAV	detection from UAV	sent to on-
	Networks and	Imagery With	imagery using deep	ground
	Learning	Deep Learning	learning techniques.	workstations or
	Systems, vol.		❖ It begins by outlining	to the cloud for
	33, no. 11, pp.		the various deep	processing rather
	6047-6067		learning architectures,	than being
	(2022)		including	implemented on
			generative	the UAV itself,
			adversarial	thereby leading
			networks	to the absence of
			autoencoders	a lightweight
			> recurrent neural	system for
			networks	vehicle
			> convolutional neural	detection.
			networks	
			and their contributions	
			to the challenge of	
			improving vehicle	
			detection.	
			The paper then focuses	
			on examining various	
			vehicle detection	
			techniques and	
	1	1		

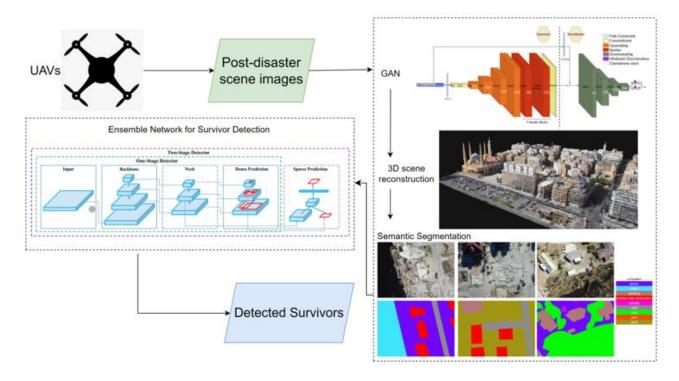
			presents different benchmark datasets and problems that have been discovered, along with possible remedies.
6.	IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-13 (2022)	Dense and Small Object Detection in UAV-Vision Based on a Global-Local Feature Enhanced Network	 ❖ This paper proposes a global-local feature-enhanced network (GLF-Net) to alleviate issues when detecting small and dense objects using UAVs. ❖ A feature-fusion module has been proposed to tackle the presence of numerous small objects. ❖ GLF-Net achieves 86.52% mean Average Precision (mAP) on the RO-UAV dataset. The scalability of the scalability of the framework is poor, and the application of GLF-Net on post-disaster UAV images leads to lower mAP, thereby requiring better
7.	IEEE/CVF International Conference on Computer Vision (ICCV), pp. 1223-1232 (2021)	Unmanned aerial vehicle visual detection and tracking using deep neural networks: A performance benchmark	 This paper executes and compares various UAV detection mechanisms using air-borne UAVs that deploy deep neural networks. ★ 4 datasets have been used and performance has been compared, namely MAV-VID, Drone-vs-Bird, Anti-UAV IR. The performance of 4 models was compared using the datasets mentioned, namely Faster RCNN, SSD512, YOLOv3, and DETR Long-distance detection of small UAVs was not taken into consideration. Deep neural networks for re-identification of UAVs were not considered as well.

8.	UMBC Student Collection (2021)	RescueNet: A High- Resolution Post Disaster UAV Dataset for Semantic Segmentation	(Detection Transformer). Overall, Faster RCNN performed best. ❖ This paper introduces a high-resolution post- disaster UAV dataset named RescueNet, which contains comprehensive pixel- level annotation of 11 classes for semantic segmentation to assess damage after a natural disaster. ❖ The dataset collection and annotation process are discussed, along with the challenges it poses. ❖ Besides that, since UAV images include only the top view of a scene, it is
			images include only
			assess the actual damage since the horizontal view also brings
			information regarding all sides of a building.
9.	IEEE/CVF Conference on	Uav-human: A large	❖ This paper proposes a UAV-Human dataset for Human
	Computer	benchmark for	human action, pose, dataset poses

	Vision and	human	and behavior a limitation
	Pattern	behavior	understanding. for attribute
	Recognition	understanding	❖ The proposed UAV- recognition
	=	_	
	(CVPR), pp.	with	
	16266-16275	unmanned	➤ 67,428 multi-modal dataset is
	(2021)	aerial vehicles	video sequences captured over
			> 119 subjects for a relatively
			action recognition long period of
			22,476 frames for time.
			pose estimation
			➤ 41,290 frames the subjects
			> 1,144 identities for have been
			person re- diversified
			identification with different
			➤ 22,263 frames for dressing types
			attribute and large
			recognition variations of
			which encourages the viewpoints
			exploration and caused by
			deployment of various multiple UAV
			data-intensive learning altitudes.
			models for UAV-based
			human behavior
			understanding.
10.	2021 IEEE	Attention-	❖ This paper proposes ❖ HRUD is a very
	International	Based	and evaluates a novel challenging
	Geoscience and	Semantic	self-attention dataset due to
	Remote Sensing	Segmentation	segmentation model its variable-
	Symposium	on UAV	named ReDNet on a sized classes
	IGARSS, pp.	Dataset for	new high-resolution along with
	2325-2328	Natural	UAV natural disaster similar
		Disaster	dataset named HRUD. textures
	(2021)		
		Damage	The challenges of among different
		Assessment	semantic segmentation different
			on the HRUD dataset classes.
			are discussed, along
			with the excellent textures of
			performance of the debris, sand,
			proposed model. and building
			with

		destruction
		damage make
		a great impact
		on the
		segmentation
		performance
		of the
		evaluated
		network
		models.

System Architecture:



Novelty:

A GAN denoiser results in images having lower occlusion and optimal brightness, thereby highlighting the important features of the object. Furthermore, using GAN improves the detection of small and dense objects, which is the case of survivors in images obtained from a UAV. A 3D reconstruction of the scene using the enhanced images obtained from the GAN-based model will be used to map and extract useful information from the scene. The GAN-based 3D reconstruction framework incorporating the Structure-From-Motion (SFM) and bundle adjustment algorithms enhances occluded survivors in the 3D model, thereby resulting in a more efficient survivor detection

mechanism compared to existing frameworks. Semantic segmentation on the 3D model leads to a pixel-level prediction of various entities or objects present in the image. The ensemble model, a hybrid architecture consisting of single-stage and multi-stage detectors, overcomes the disadvantages of both frameworks. Deploying an ensemble network comprising the CenterNet and Cascade R-CNN frameworks improves the performance and efficiency of survivor detection. The overall framework will increase the accuracy and performance of the survivor detection task, thereby resulting in efficient Search-And-Rescue operations.

Expected Outcomes:

- ❖ To develop an efficient post-disaster scene understanding framework using UAVs for survivor detection and Search-And-Rescue (SAR) operations.
- ❖ To deploy a Generative Adversarial Network (GAN) framework to improve the detection of survivors, who are generally present as small and dense objects in post-disaster UAV images. A GAN denoiser will result in images having lower occlusion and optimal brightness, thereby highlighting the important features of the object.
- ❖ To devise a 3D scene-reconstruction mechanism based on the Structure-From-Motion (SFM) and bundle adjustment algorithms using images obtained from a swarm of UAVs to map and extract useful information from the scene.
- ❖ To deploy a semantic segmentation mechanism on the 3D model, leading to a pixel-level prediction of various entities or objects in the 3D model. This will improve the detection of survivors present in the post-disaster scene.
- ❖ To implement a hybrid single-stage and multi-stage ensemble network for survivor detection on the previously obtained semantic entities. The model will comprise the CenterNet and Cascade R-CNN mechanisms to combine the benefits of both, thereby decreasing the high false negative rate of multi-stage mechanisms and improving the performance of singlestage detectors.

References:

- 1. J. Dong, K. Ota and M. Dong, "UAV-Based Real-Time Survivor Detection System in Post-Disaster Search and Rescue Operations," in *IEEE Journal on Miniaturization for Air and Space Systems*, vol. 2, no. 4, pp. 209-219, 2021
- 2. H. Ren et al., "Swarm UAV SAR for 3-D Imaging: System Analysis and Sensing Matrix Design," in IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1-16, 2022
- **3.** T. C. Bybee and S. E. Budge, "Method for 3-D Scene Reconstruction Using Fused LiDAR and Imagery From a Texel Camera," in IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 11, pp. 8879-8889, Nov. 2019
- **4.** Albaba, Berat Mert, and Sedat Ozer, "SyNet: An ensemble network for object detection in UAV images," in 25th IEEE International Conference on Pattern Recognition (ICPR), pp. 10227-10234, 2021
- **5.** A. Bouguettaya, H. Zarzour, A. Kechida and A. M. Taberkit, "Vehicle Detection From UAV Imagery With Deep Learning: A Review," in *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 11, pp. 6047-6067, Nov. 2022
- **6.** T. Ye, W. Qin, Y. Li, S. Wang, J. Zhang and Z. Zhao, "**Dense and Small Object Detection in UAV-Vision Based on a Global-Local Feature Enhanced Network**," in *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1-13, 2022
- 7. Rahnemoonfar, Maryam, Tashnim Chowdhury, and Robin Murphy. "RescueNet: A High-Resolution Post Disaster UAV Dataset for Semantic Segmentation." *UMBC Student Collection*, 2021
- **8.** T. Chowdhury and M. Rahnemoonfar, "Attention Based Semantic Segmentation on UAV Dataset for Natural Disaster Damage Assessment," 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, pp. 2325-2328, 2021
- 9. Li, Tianjiao, Jun Liu, Wei Zhang, Yun Ni, Wenqian Wang, and Zhiheng Li. "Uav-human: A large benchmark for human behavior understanding with unmanned aerial vehicles." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 16266-16275, 2021
- **10.** Isaac-Medina, Brian KS, Matt Poyser, Daniel Organisciak, Chris G. Willcocks, Toby P. Breckon, and Hubert PH Shum. "**Unmanned aerial**

performance ben	vehicle visual detection and tracking using deep neural networks: performance benchmark." In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), pp. 1223-1232, 2021.				