

Introduction

Thermal multispectral imagery is imperative for a plethora of environmental applications. Unfortunately, there are no publicly-available datasets of thermal multispectral images with a high spatial resolution that would enable the development of algorithms and systems in this field. To tackle this issue, we designed a narrow-band (monochromatic) thermal image generator, conditioned on a wide-band (panchromatic) input image. We further augmented the model with physically modeled prior information to improve the model's training stability and increase its output's fidelity. Our contributions are:

- Introduction of a novel thermal aerial images dataset with unpaired images of different spectral bands.
- Application of UI2I between different thermal image modalities;
- Development and utilization of an analytic-physical-UI2I translation model;

Thermal Aerial Multispectral Dataset

The data for training our model was collected using a lightweight airplane, 2000 meters above ground. The plane conducted several flights, each with some IR filter (monochromatic) or without (panchromatic).



Due to the nature of flight conditions, data collected for each channel is inherently unpaired to the others, which led us toward developing an UI2I solution.

Physical background

- **Blackbody Radiation:** electromagnetic emission of an ideal opaque object due to its temperature, described by the Stephan-Boltzmann equation:

$$P(T) = \int_0^\infty \frac{2\pi hc^2}{\lambda^5} \frac{1}{e^{\frac{hc}{\lambda T}} - 1} d\lambda = \frac{\sigma}{\pi} T^4 \quad [Wsr^{-1}m^{-2}]$$

- Thermal image intensity depends on the both the object's temperature (T_{obj}) and the camera's intrinsic temperature (T_{int}). Nugent et al. [1] suggested 3rd order polynomials for the dependency in the ambient temperature:

$$I(T_{obj}, T_{int}) = p_c^{(0)}(T_{int})T_{obj}^4 + p_c^{(1)}(T_{int})$$

$$p_c^{(i)}(T_{int}) = \sum_{k=0}^3 c_{i,k} T_{int}^k$$



Method

Physical UI2I model

We rely on Nugent et al.'s theorem to calibrate 2 physical polynomial transformations:

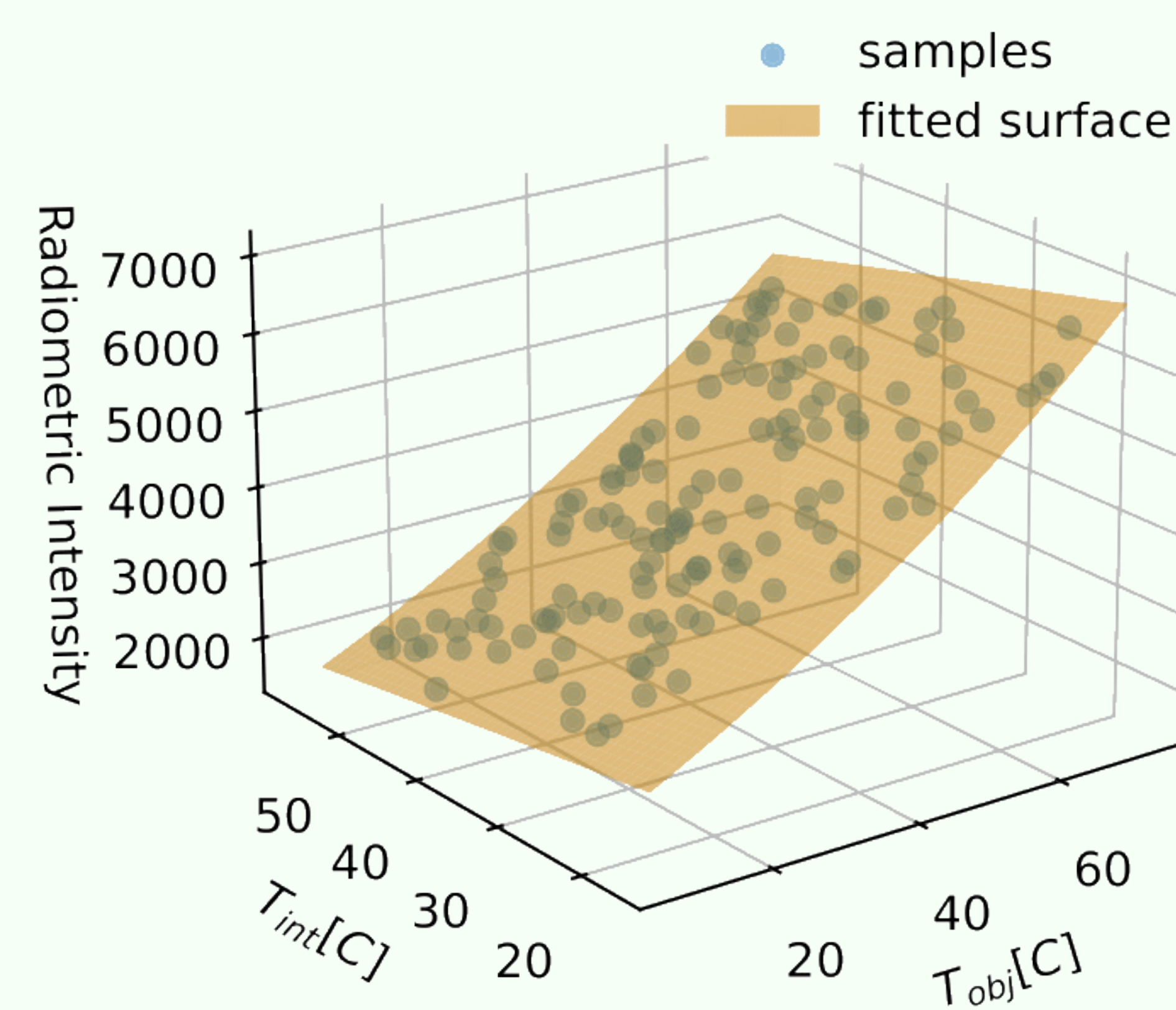
- Transformation of panchromatic intensities to object temperatures:

$$\hat{T}_{obj} = \sqrt[4]{\frac{I_{pan} - p_{c_{pan}}^{(0)}(T_{pan})}{p_{c_{pan}}^{(1)}(T_{pan})}}$$

- Transformation of object temperatures to monochromatic intensities.

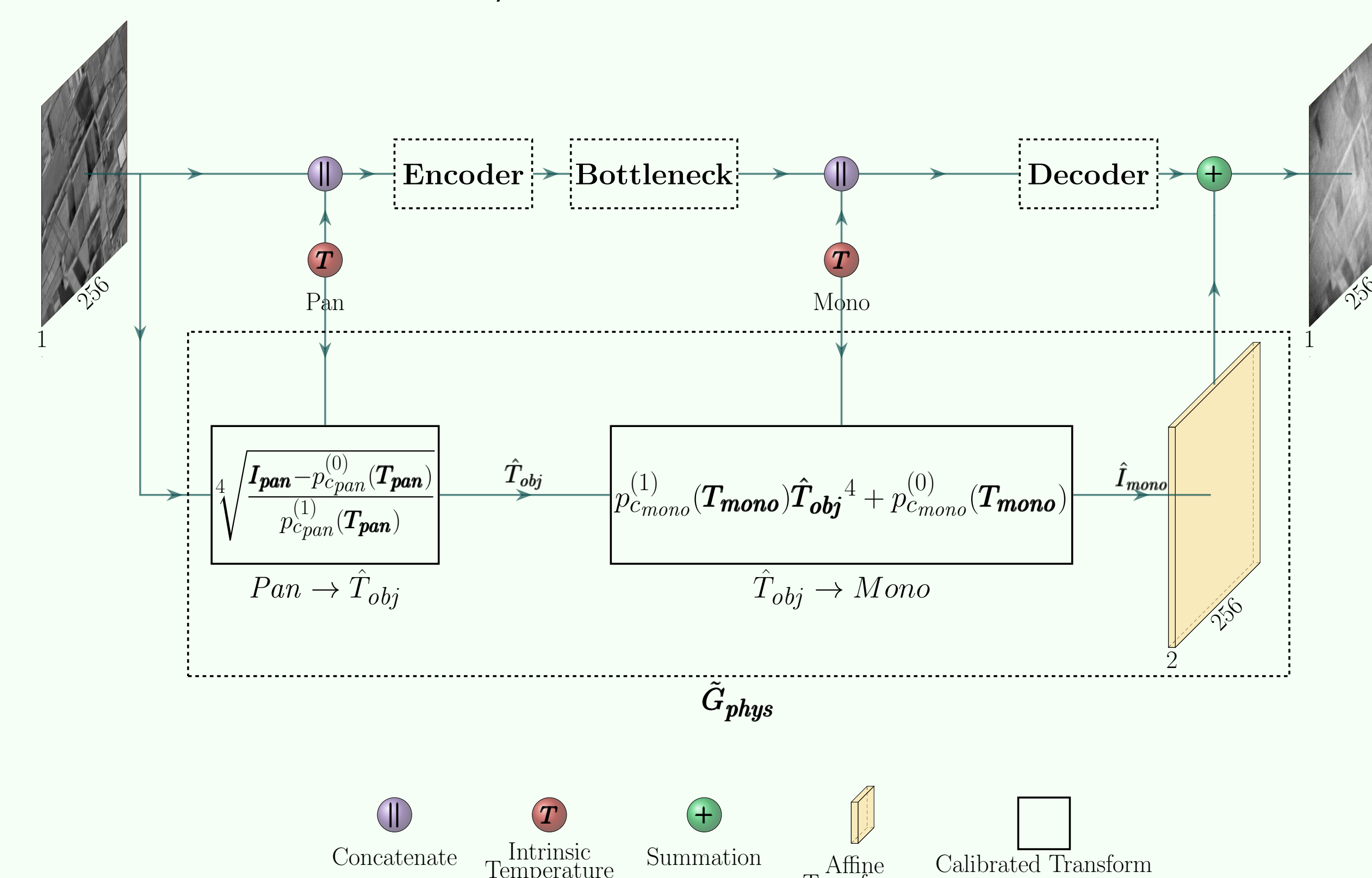
$$\hat{I}_{mono} = p_{c_{mono}}^{(1)}(T_{mono})\hat{T}_{obj}^4 + p_{c_{mono}}^{(0)}(T_{mono})$$

The two transformations are cascaded to get a complete panchromatic to monochromatic UI2I model.



PETIT

Our physical UI2I model is fused with a deep generative adversarial network (GAN) generator, who's architecture is based on those of CycleGAN [3] and CUT [2].



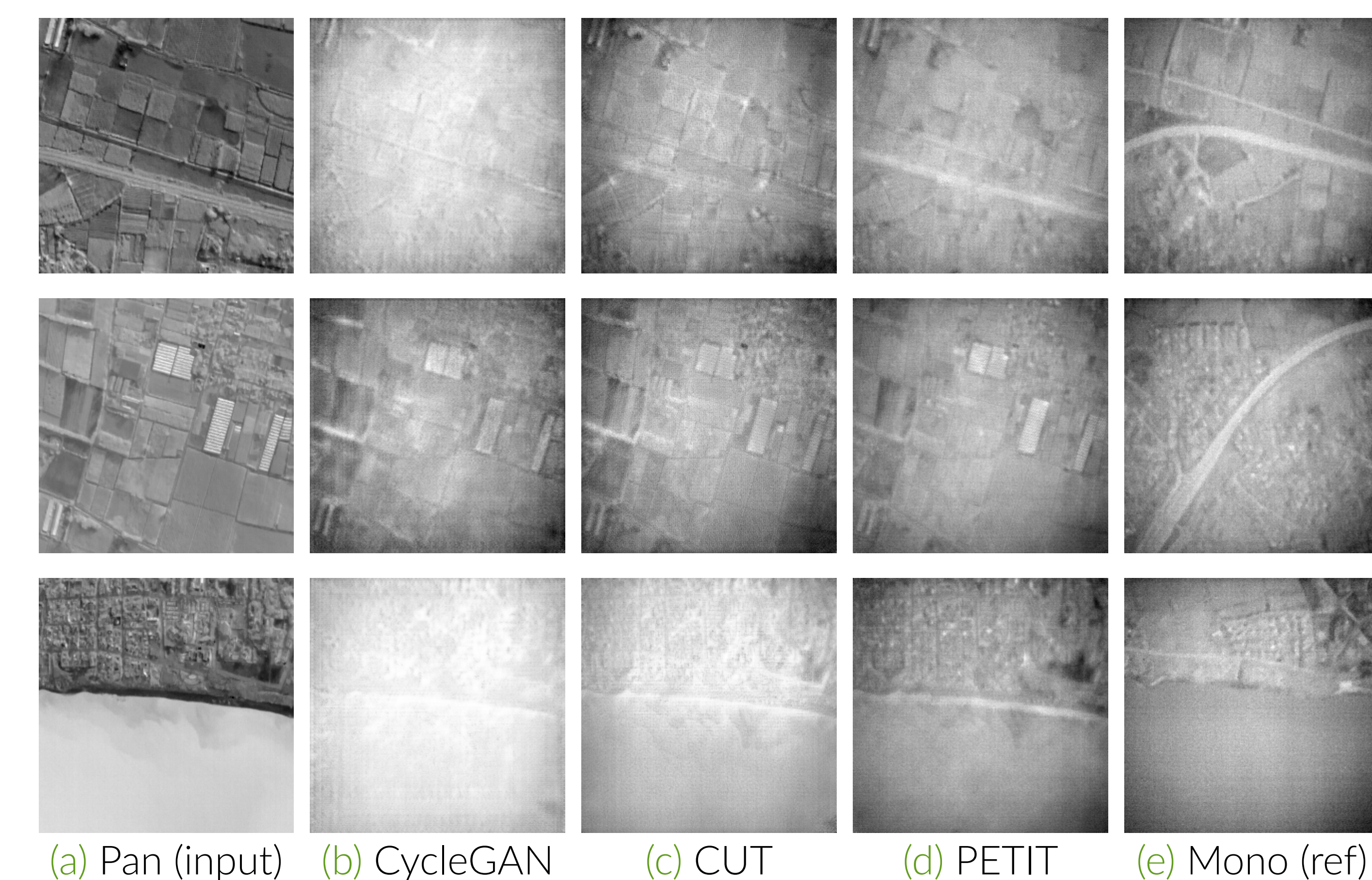
The physical estimator is used to produce a raw approximation of the desired output, leaving the deep estimator with the task of predicting the finer residual details.

Quantitative Results

	Configuration			FID	
	Backbone	Int Phys	Caption	Mean	Std
CycleGan		X	X	Baseline	51.05 9.82
		X	✓		35.54 3.72
		✓	X	PETIT	50.17 8.89
CUT		✓	✓	PETIT	33.8 1.23
		X	X	Baseline	38.43 1.52
		X	✓		29.85 0.99
		✓	X		48.88 1.46
	✓	✓	PETIT	27.35 1.01	

Qualitative Results

In accordance with the quantitative results, the monochromatic outputs produced by PETIT seem to be of superior quality compared to all other configurations. Generally speaking, PETIT's outputs incur less spurious artifacts and exhibit stronger fidelity to real monochromatic modality.



Conclusions

- Physical modeling is beneficial for thermal UI2I translation.
- PETIT beats deep SOTA UI2I models both quantitatively (by $\approx 50\%$!) and qualitatively.
- Fidelity of generated monochromatic images is good enough for synthesizing an artificial multispectral dataset.

References

- [1] Paul W. Nugent, Joseph A. Shaw, and Nathan J. Pust. Correcting for focal-plane-array temperature dependence in microbolometer infrared cameras lacking thermal stabilization. *Optical Engineering*, 52(6):1 - 8, 2013.
- [2] Taesung Park, Alexei A. Efros, Richard Zhang, and Jun-Yan Zhu. Contrastive learning for unpaired image-to-image translation. In *European Conference on Computer Vision*, 2020.
- [3] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Computer Vision (ICCV), 2017 IEEE International Conference on*, 2017.