CVPR'21 Workshop "Vision for All Seasons: Adverse Weather and Lighting Conditions"

Workshop at CVPR21 <link>

1

Keynote - Prof. Wolfram Burgard: Exploiting Knowledge from Multiple Modalities for Robust Perception

1.A

Idea of Using Thermal Cameras for Transfering Capabilities from Day Time to Night Time

PowerPoint Slide Show – [all_seansons]

Exploiting Knowledge from Multiple Modalities for Robust Perception

Wolfram Burgard

Joint work with: Jannik Zürn, Johan Vertens, Kshitij Sirohi, Rohit Mohan, Abhinav Valada …

UNI FREIBURG

AiS Autonomous Intelligent Systems

Motivation

- We want to minimizie labeling efforts
  - New tasks
  - Domain transfer

- In this talk: **using multi-modal setups**

PowerPoint Slide Show – [all_seansons]

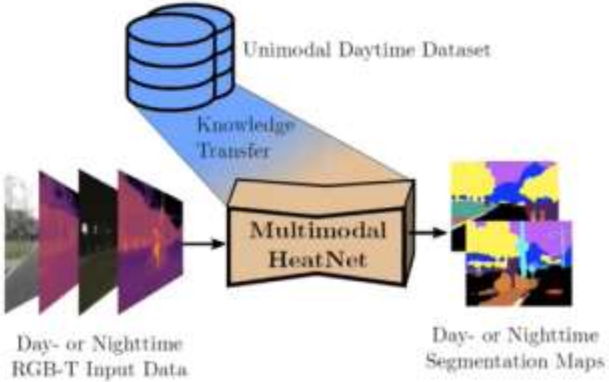
Robust Semantic Segmentation by Domain Adaption

HeatNet: Bridging the Day-Night Domain Gap in Semantic Segmentation with Thermal Images

arXiv:2003.04645v1 [cs.CV] 10 Mar 2020

I. INTRODUCTION

HeatNet: Bridging the Day-Night Domain Gap in Semantic Segmentation with Thermal Images. Johan Vertens, Jannik Zürn and Wolfram Burgard, IROS 2020



INSIGHTS

- IRIS Published.

- Focused on - how we can actually leverage - the thermal cameras - for better semantic segmentation, in particular, - for situations - where normal RGB cameras face difficulty - like the low light vision.

- Labelling nighttime images is very difficult for semantic segmentation task.

Motivation

Semantic segmentation prediction during nighttime using a conventional CNN trained on publicly available datasets

Labeling night-time images is extremely painful!

INSIGHTS

- The idea of this work is - to leverage daytime semantic segmentation AND another modality - to bootstrap semantic segmentation for nighttime.

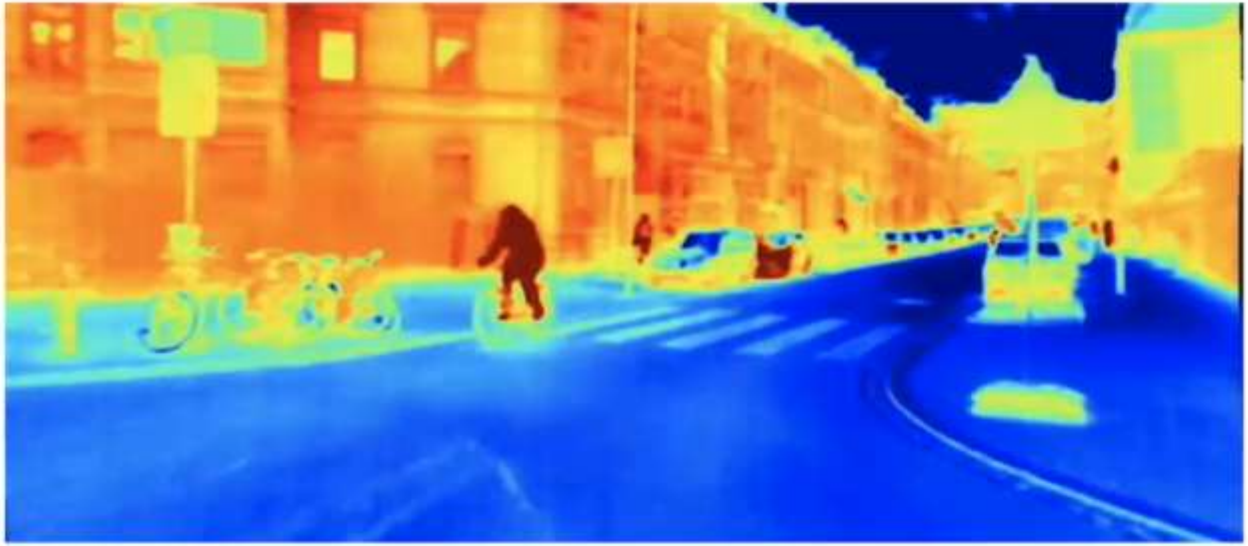
- NEXT SLIDE - A Typical Night Scene

- AND THEN - Overlaying with Thermal Infrared Images.

Motivation

Thermal infrared images exhibit small domain gap between day- and nighttime

Motivation



Thermal infrared images exhibit small domain gap between day- and nighttime

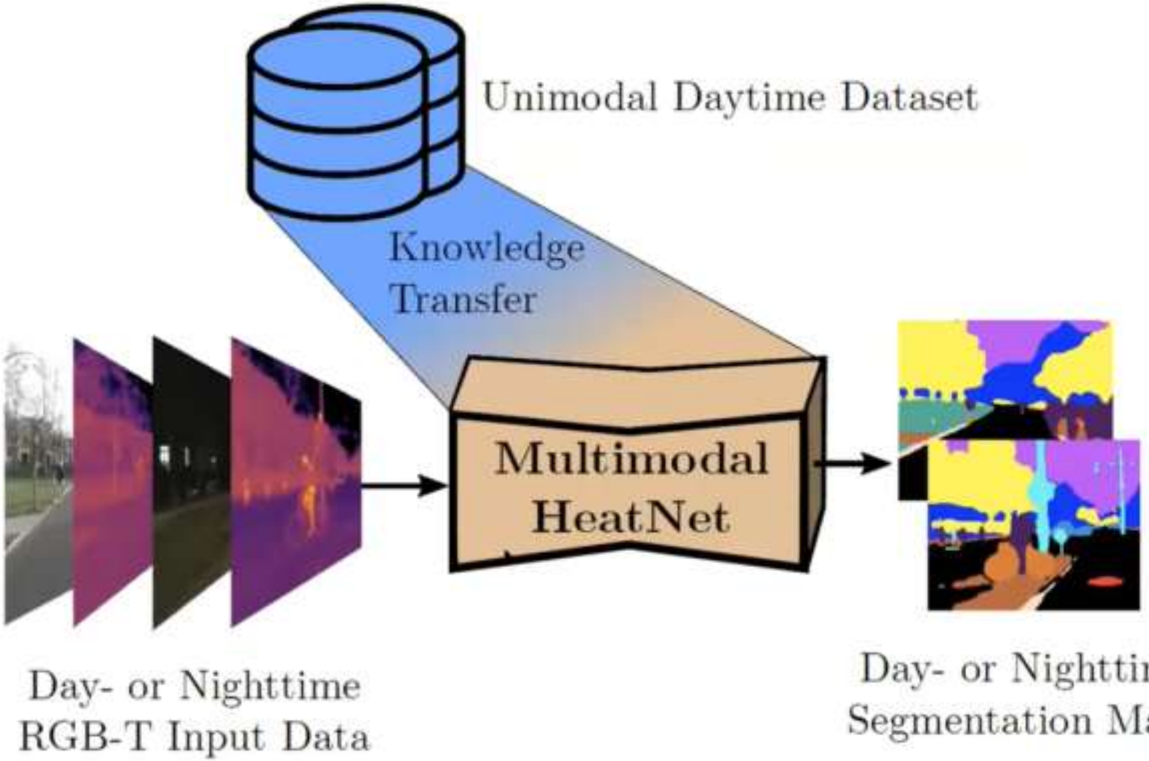
INSIGHTS

- THERMAL INFRARED IMAGES exhibit small domain gap between day and night time.

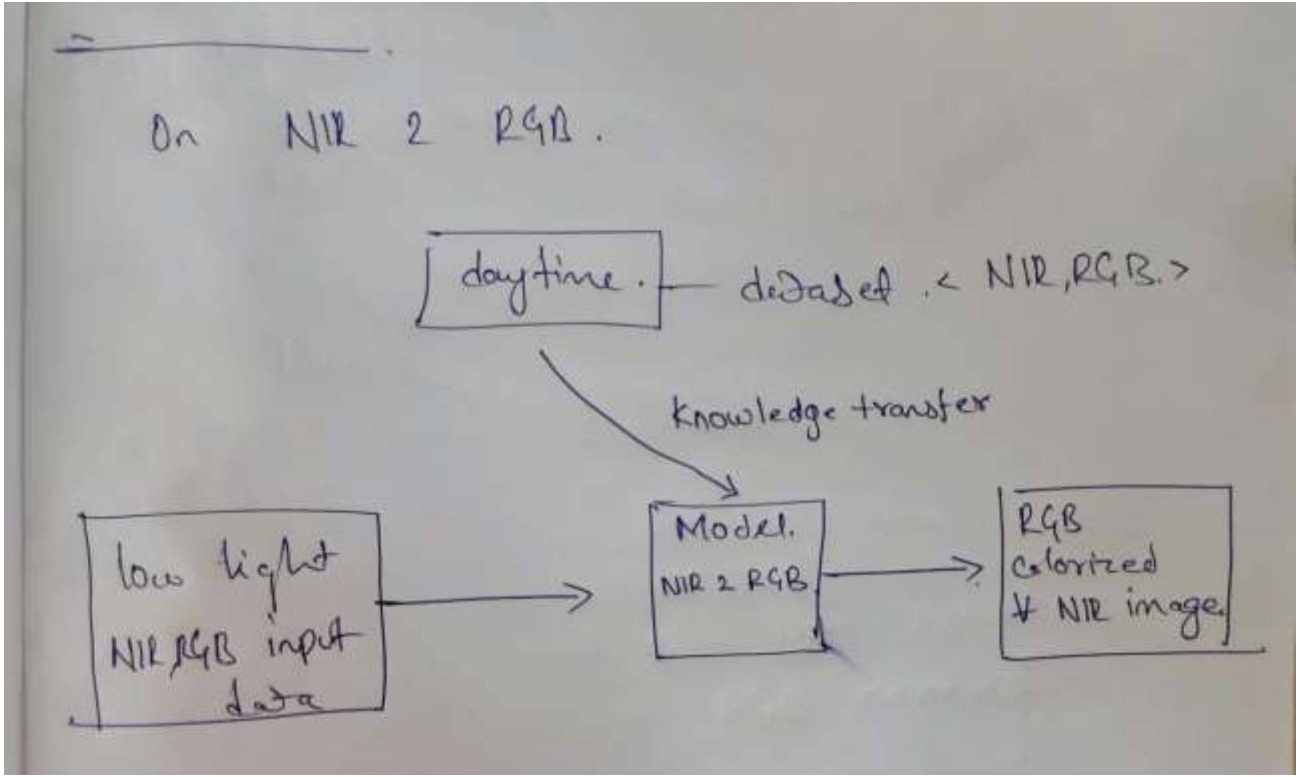
- **NEXT SLIDE :** Shows the Approach - To Train a Multimodal HeatMap - That takes RGB - Thermal Images - AND - Creates Semantic Segmentation Map - For Day & Night time Images.

- At the same time, - have to leverage all the knowledge we have - for Daytime Semantic Segmentation.

Approach

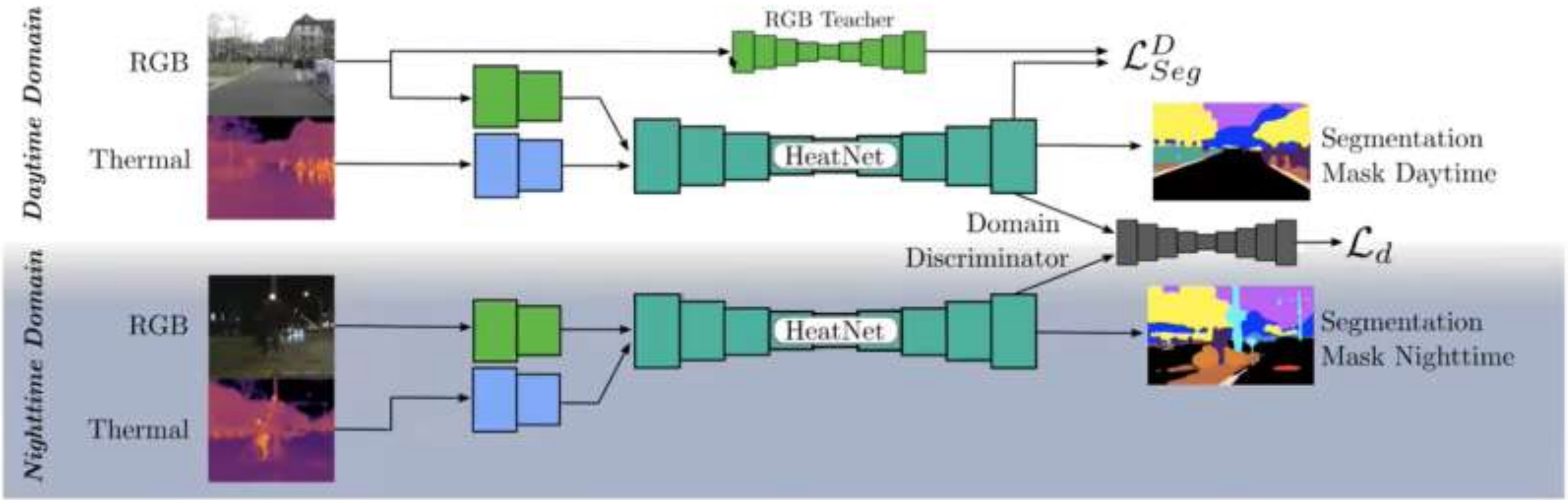

Unimodal Daytime Dataset
Knowledge Transfer
Multimodal HeatNet
Day- or Nighttime RGB-T Input Data
Day- or Nighttime Segmentation Maps

INSIGHTS


On NIR 2 RGB.
daytime.
dataset .< NIR, RGB.>
knowledge transfer
low light NIR RGB input data
Model. NIR 2 RGB
RGB Colorized ¥ NIR image

PowerPoint Slide Show – [all_seansons]

Approach



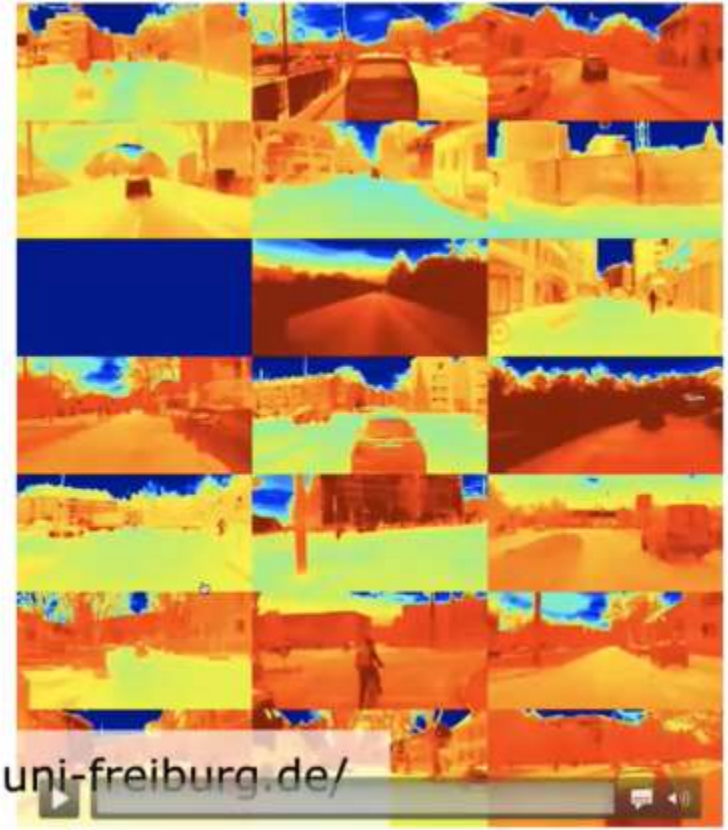
$$\mathcal{L}_{p_1} = \mathcal{L}_s^D + \lambda[0 - C(S_N)]^2, \qquad \mathcal{L}_{p_2} = \frac{1}{HW}\sum_{h,w}\begin{cases}[0 - C(S_X)]^2, & \text{if } X = D\\ [1 - C(S_X)]^2, & \text{if } X = N\end{cases}$$

Dataset

- Freiburg Thermal Dataset
- Five day- and three nighttime collections
- Multiple seasons
- 12,000 daytime images
- 8,000 nighttime images
- GPS and IMU data
- LiDAR point clouds
- 64 evaluation images

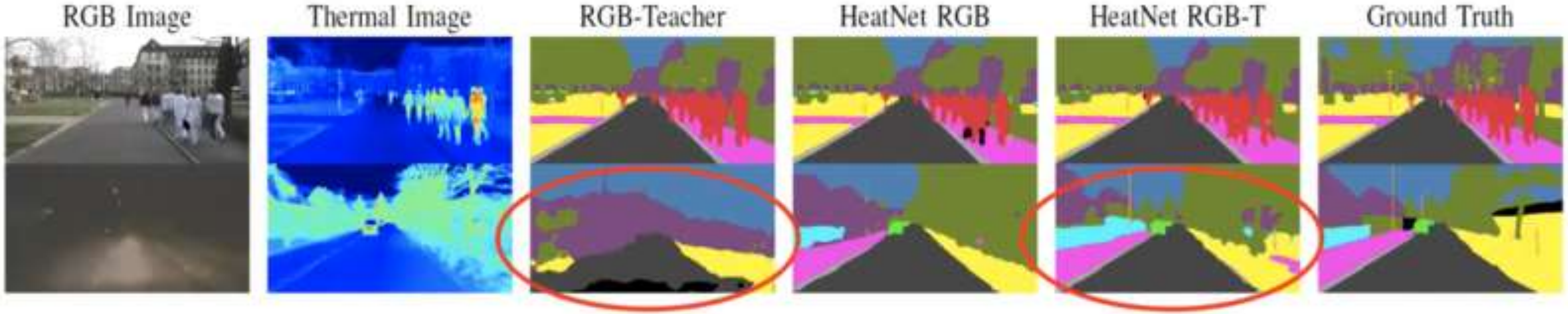
PowerPoint Slide Show – [all_seansons]

Dataset

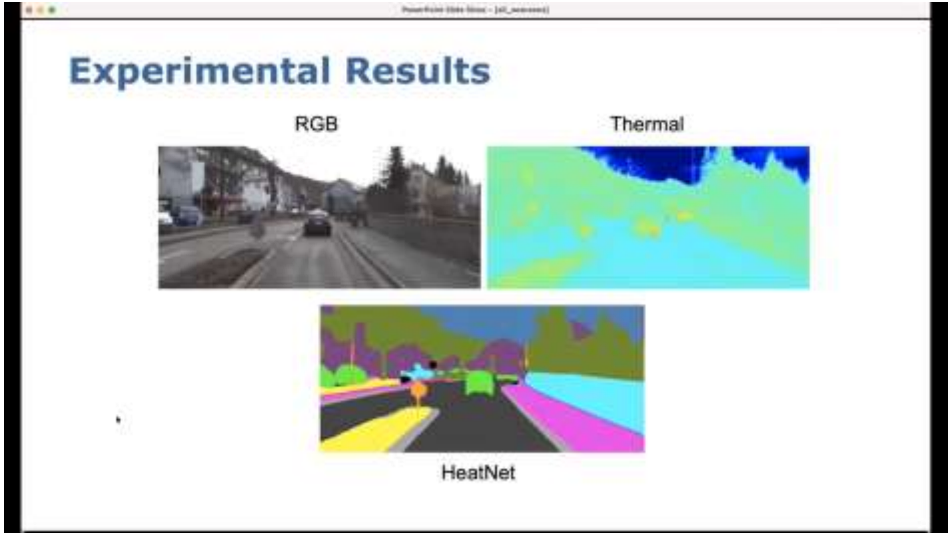


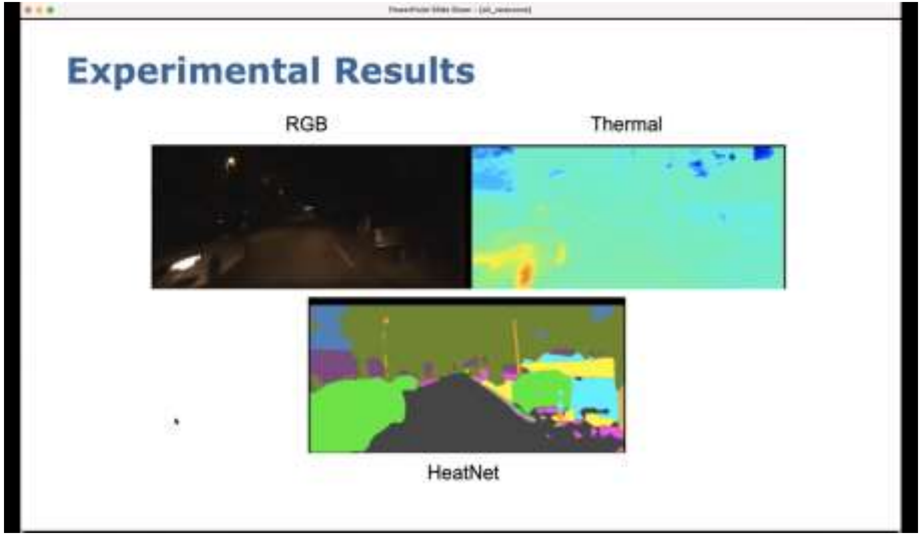
http://thermal.cs.uni-freiburg.de/

Experimental Results



DAYTIME AND NIGHT TIME





INSIGHTS

Instead of Daytime and Nighttime, we can do for without rain and in the rain.

Quantitative Evaluation

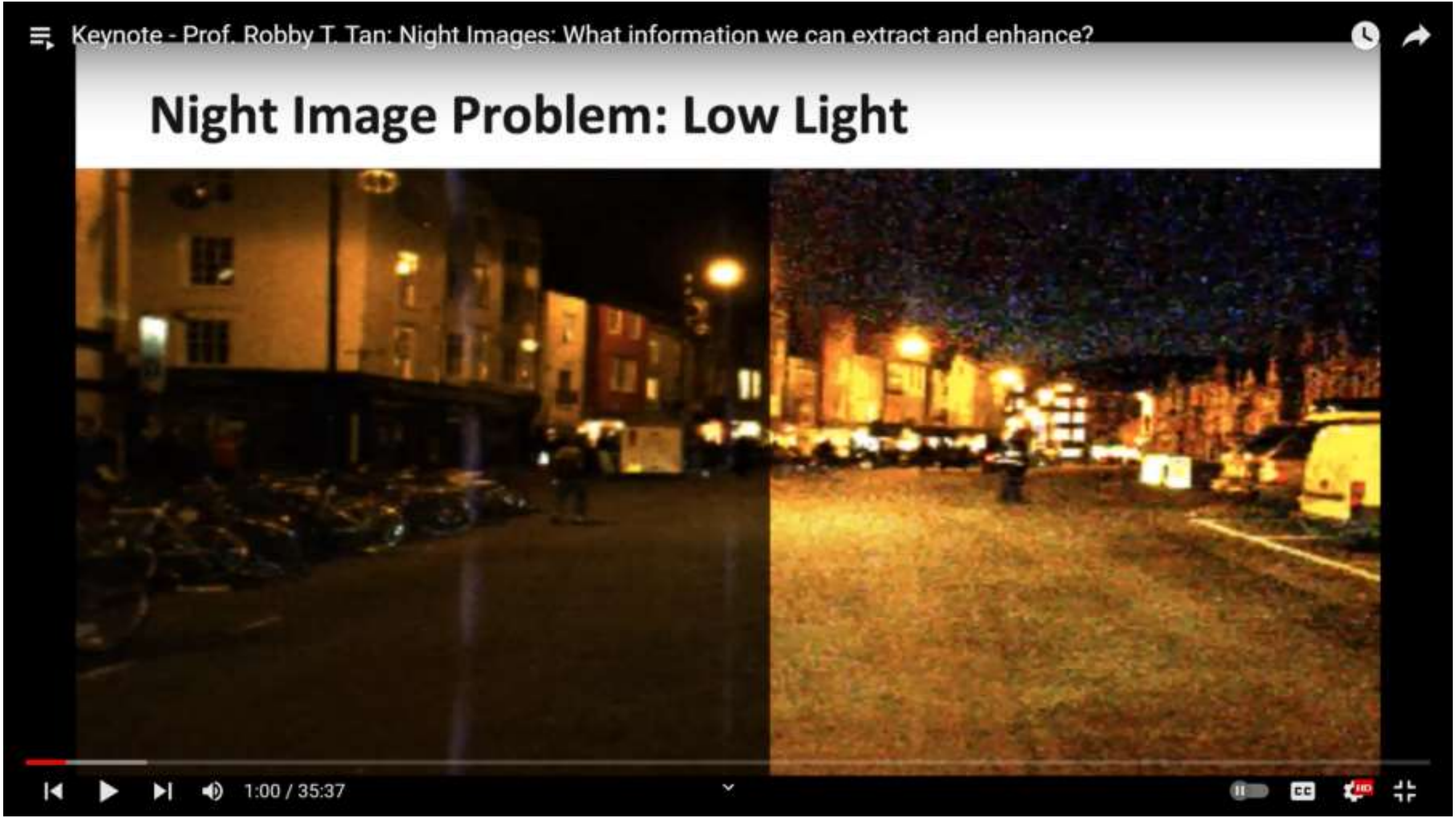
Train On	Test On	Model	RGB	T	Road	Sidewalk	Building	Curb	Fence	Pole	Vegetation	Terrain	Sky	Person	Car	Bicycle	Mean
MF	MF	MFNet [9]	✓	✓	-	-	-	-	-	-	-	-	-	58.9	65.9	42.9	55.9
		RTFNet-50 [25]	✓	✓	-	-	-	-	-	-	-	-	-	**67.8**	**86.3**	**58.2**	**70.7**
		HeatNet	✓	✓	-	-	-	-	-	-	-	-	-	56.4	68.8	33.9	53.0
	FR-T Day/Night	MFNet [9]	✓	✓	-	-	-	-	-	-	-	-	-	42.8	27.0	24.5	31.4
		RTFNet-50 [25]	✓	✓	-	-	-	-	-	-	-	-	-	**63.2**	61.5	51.3	58.6
		HeatNet	✓	✓	86.7	57.5	67.7	46.4	41.5	43.8	57.9	44.1	63.7	63.1	**85.6**	**58.2**	59.7
FR-T	MF	HeatNet	✓	✓	-	-	-	-	-	-	-	-	-	51.6	61.8	30.2	47.9
(Vistas)	FR-T Day	RGB Teacher	✓	✗	**89.7**	**67.0**	73.8	56.9	48.8	53.8	73.8	62.8	84.3	72.0	90.1	60.4	69.4
FR-T		HeatNet	✓	✓	89.4	65.6	**74.8**	**59.7**	**52.9**	**54.3**	**74.1**	**65.1**	**84.5**	**74.0**	**91.2**	**64.1**	**70.8**
FR-T	FR-T Night	Thermal Teacher	✗	✓	84.9	60.5	**65.5**	43.1	31.8	38.1	51.8	40.1	72.6	49.6	**87.1**	**56.9**	57.0
(Vistas)		RGB Teacher	✓	✗	76.3	22.6	53.4	10.8	14.1	31.6	10.4	13.5	47.7	28.0	74.3	45.2	35.7
FR-T		HeatNet	✓	✓	**86.4**	**60.9**	65.4	**45.5**	**35.5**	**42.0**	**52.5**	**52.3**	**73.9**	**54.9**	85.7	53.3	**59.0**
FR-T	FR-T Day/Night	HeatNet	✓	✓	**87.9**	**63.3**	**70.1**	**52.6**	**44.2**	**48.2**	**63.3**	**58.9**	**79.2**	**64.5**	**88.5**	**58.7**	**64.9**
FR-T		HeatNet RGB-only	✓	✗	82.7	56.0	66.0	45.3	34.0	37.8	58.4	49.5	71.0	54.4	84.2	57.4	58.0
(Vistas)	BDD Night [34]	RGB Teacher	✓	✗	68.8	21.5	32.9	-	0.0	12.3	11.5	6.6	**27.2**	24.5	40.4	-	24.6
FR-T		HeatNet RGB-only	✓	✗	**87.1**	**40.0**	**50.2**	-	**25.9**	**22.9**	**12.8**	**8.5**	25.0	**27.4**	**68.3**	-	**36.8**

2

NIGHT IMAGES: WHAT INFORMATION WE CAN EXTRACT & ENHANCE?

INSIGHTS

- Night Images Problem - LOW LIGHT
- **WHAT IF** we multiply the pixels with some constant values?
    - NOISY IMAGES
    - INTERESTINGLY – NOISE CAN BE DIFFERENTIATED FROM STRUCTURES


Keynote - Prof. Robby T. Tan: Night Images: What information we can extract and enhance?
Night Image Problem: Low Light
1:00 / 35:37

INSIGHTS

- Night Images Problem: Glow/ Glare/ Floodlight.

Night Image Problem: Uneven Light Distribution

Night Image Problem: Light Colors

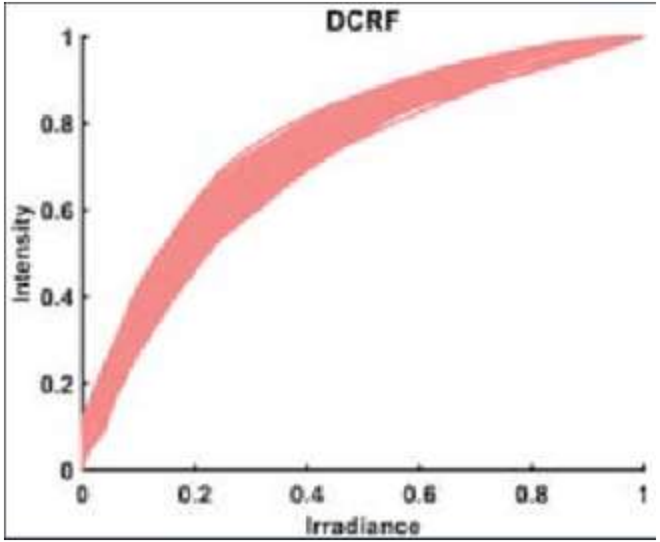
INSIGHTS - **NIGHT IMG ENHANCEMENT**

- Camera response function (CRF) relates scene irradiance to image intensities.
  - Estimation of CRF is a fundamental and necessary step in many computer vision applications such as the generation of high dynamic image, bidirectional reflectance distribution function (BRDF) estimation etc.
  - CRF is non-linear.
- Irradiance vs Radiance
  - In terms of explanation, it can be said that Radiation is the number of photons that are being emitted by a single source. Irradiation, on the other hand, is one where the radiation is falling on the surface is being calculated.
- **IDEA : BOOST the intensity, BUT have to keep the color => ESTIMATE THE**

INSIGHTS - **NIGHT IMG ENHANCEMENT**

- NOT JUST BOOST THE IMAGE -
- HAVE TO SUPPRESS LIGHT IN IMGS LIKE THIS
- HAVE TO REMOVE GLARE HERE

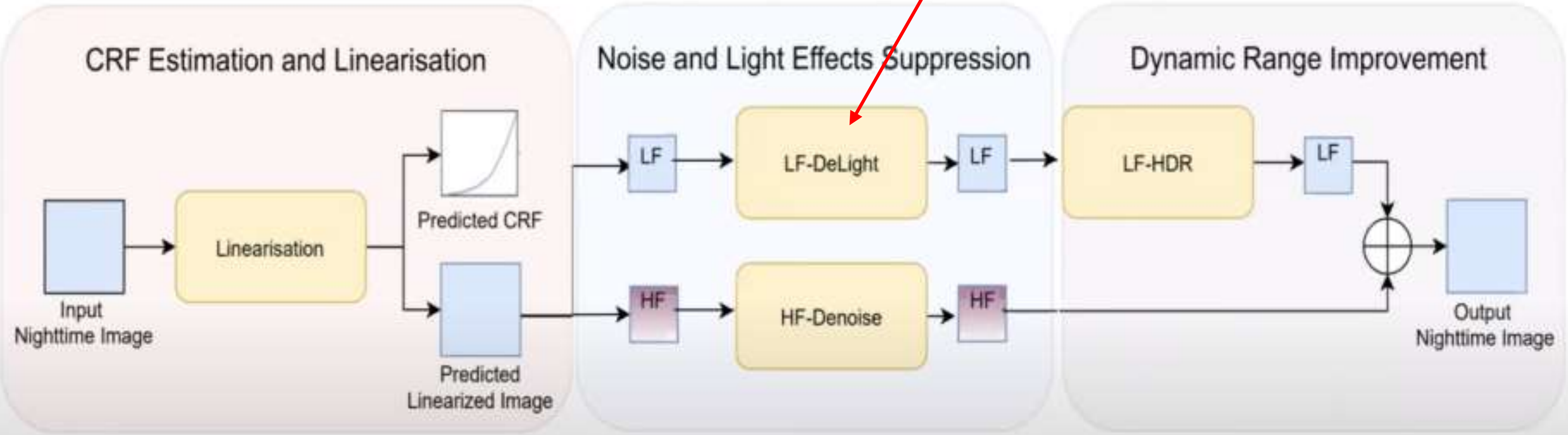
CRF of Camera



Problem: Boosting low light regions, at the same time suppress glare and noise

Pipeline

De Glare



Published in CVPR'21

HDR

- HDR stands for high dynamic range.
- Put simply, *it's the range of light and dark tones in your photos*.
- The human eye has a very high dynamic range — which is why we can see details in both shadows and highlights.

Supervised Training: CRF

- CRF Loss:

$$\mathcal{L}_{\text{mse}} = \|\hat{\mathbf{g}} - \mathbf{g}^{gt}\|_2 \qquad\qquad \hat{\mathbf{g}} = \mathbf{g_0} + \sum_{i=1}^{11} \mathbf{h}_i \mathbf{c}_i$$

- Image-Linearization Loss:

$$\mathcal{L}_{\text{lin}} = \|\hat{\mathbf{g}}(\mathbf{Z}') - \mathbf{g}^{gt}(\mathbf{Z}')\|_1$$

Supervised Training: HDR

- For decomposing the linearized image to low and high frequency layers, we employ: 'Fast end-to-end trainable guided filter', CVPR'18.
- HDR Loss:

$$\mathcal{L}_{\text{HDR}} = \left\| \frac{\log(1+\mu\hat{\mathbf{X}})}{\log(1+\mu)} - \frac{\log(1+\mu\mathbf{X}^{gt})}{\log(1+\mu)} \right\|_1$$

$$\hat{\mathbf{X}} = \frac{1}{K}\sum_{k=1}^{K}(\mathbf{HrLF}_{\mathbf{X}^k} + \mathbf{DnHF}_{\mathbf{X}^k})$$

Loss function is based on μ-law (used for tone mapping)

X is an HDR image; K is the number of filters

Unsupervised Test-Time Training: CRF

- CRF-Monotonicity Loss:

$$\mathcal{L}_{\text{mon}} = \sum_{t=0}^{1} H\left(-\frac{\partial \hat{\mathbf{g}}(t)}{\partial t}\right)$$

- CRF-Pixel-Linearization Loss:

$$\mathcal{L}_{es} = \sum_{i=1}^{S}\left(\frac{|\mathbf{n}_{\mathbf{Y}es}^{\text{min}} - \mathbf{n}_{\mathbf{Y}es}^{\text{max}}| \times |\mathbf{n}_{\mathbf{Y}es}^{\text{min}} - \mathbf{n}_{\mathbf{Y}es}^{\text{i}}|}{|\mathbf{n}_{\mathbf{Y}es}^{\text{min}} - \mathbf{n}_{\mathbf{Y}es}^{\text{max}}|}\right),$$

$$\mathcal{L}_{\text{distlin}} = \sum_{e=1}^{E}\left(\sum_{s=1}^{S}(\mathcal{L}_{es})\right),$$

E = #patches; Each patch has a size of S x S

Light Effect Suppression:

(**a**) Input

(**b**) LF Map

(**d**) LF Map (w/o l. e.)

(**e**) Output (w/o l. e.)

Results:

Input | **Our Method** | Ground-Truth

HDRCNN [2] | SingleHDR [10] | DrTMO [3]

Results:

Input

Our Method

LIME [6]

ZeroDCE [5]

EnlightenGAN [7]

SingleHDR [10]

Results:

GLARE

Input Image

Our Method

LIME [6]

ZeroDCE [5]

EnlightenGAN [7]

SingleHDR [10]

Keynote - Prof. Robby T. Tan: Night Images: What information we can extract and enhance?

Publications:

- Nighttime Haze Removal with Glow and Multiple Light Colors ICCV’15
- Nighttime Defogging Using High-Low Frequency Decomposition and Grayscale-Color Networks, ECCV’20
- Single-Image Camera Response Function Using Prediction Consistency and Gradual Refinement, ACCV’20
- Nighttime Stereo Depth Estimation using Joint Translation-Stereo Learning: Light Effects and Uninformative Regions, 3DV’20
- Nighttime Visibility Enhancement by Increasing the Dynamic Range and Suppression of Light Effects, CVPR’21.

NIGHTTIME HAZE REMOVAL WITH GLOW AND MULTIPLE LIGHT COLORS

- 2015 IEEE International Conference on Computer Vision.
- This paper focuses on dehazing nighttime images.

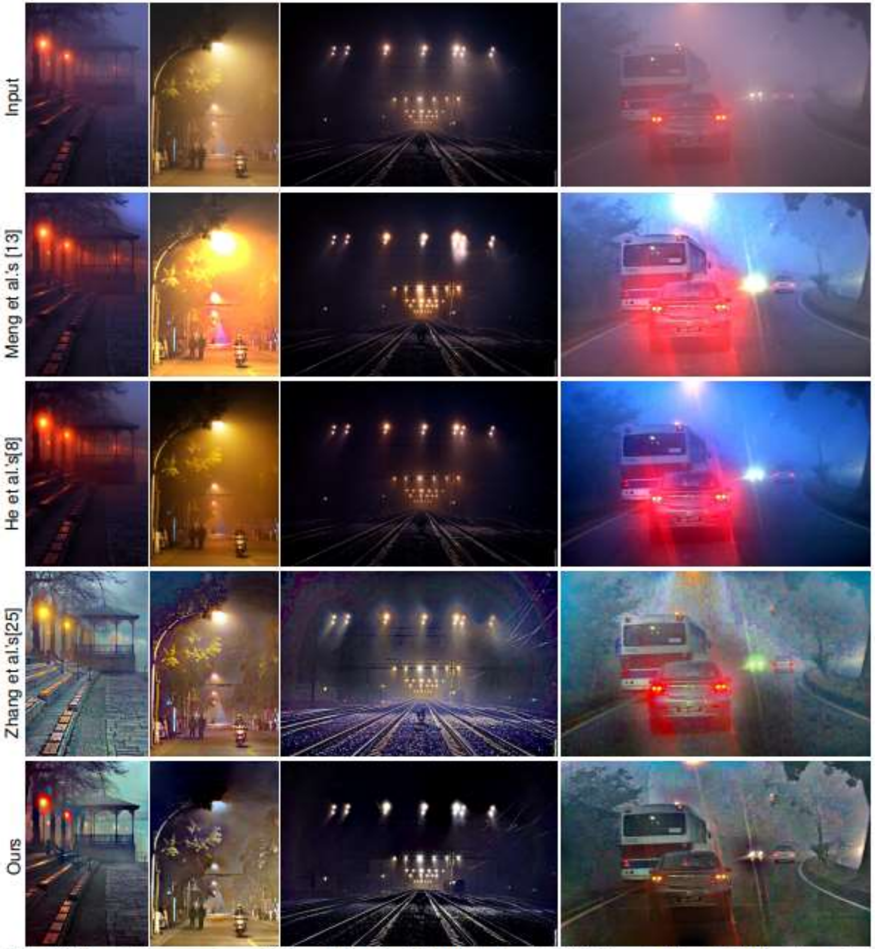


Figure 10. The qualitative comparisons of Meng et al.'s method [13], He et al.'s method [8], Zhang et al.'s method [25], and ours using various nighttime images.

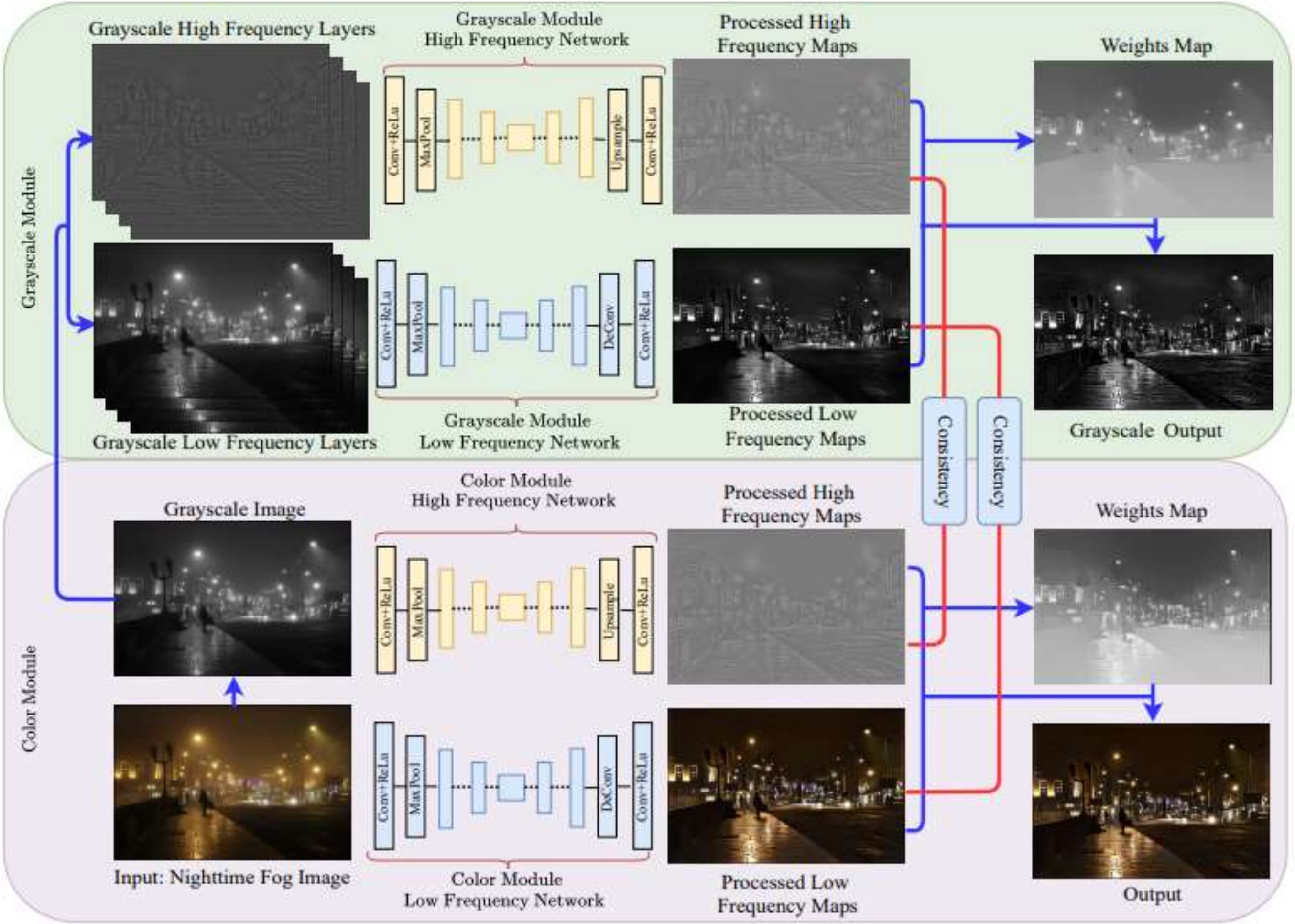
NIGHTTIME DEFOGGING USING HIGH-LOW FREQUENCY DECOMPOSITION AND GRAYSCALE-COLOR NETWORKS

- We address the problem of nighttime defogging from a single image by introducing a framework consisting of two modules: grayscale and color modules.

European Conference on
Computer Vision
ECVV 2020

M O D E L

P I P E L I N E



Input Image

Our Result

Li et al. [17]

Zhang et al. [26]

Ancuti et al. [1]

EPDN [21]

Input Image

Our Result

Li et al. [17]

Zhang et al. [26]

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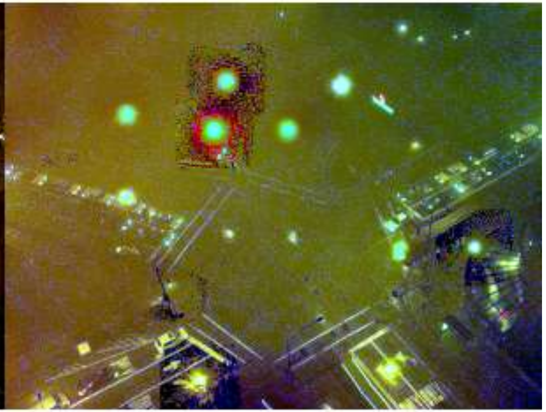
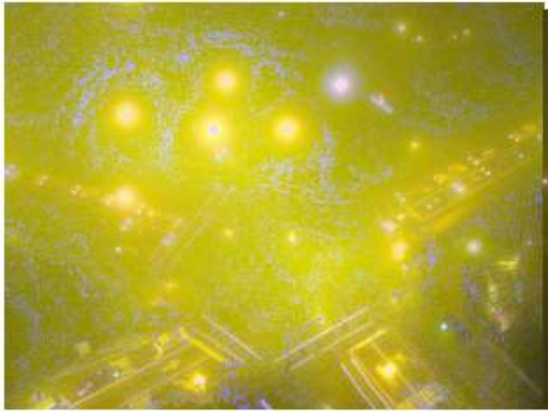
Input Image

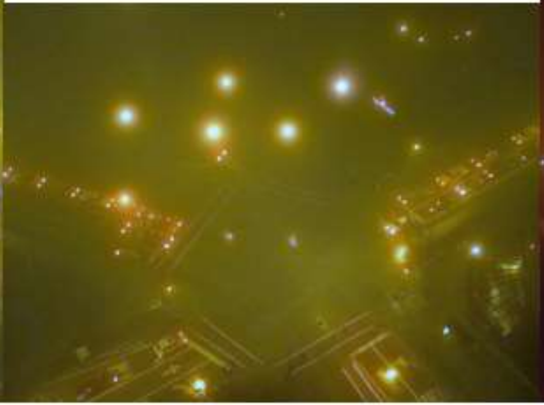
Our Result



Li et al. [17]



Zhang et al. [26]



Ancuti et al. [1]

EPDN [21]

<LINK2PAPER>

6 Conclusion

We have introduced a learning-based nighttime defogging method. To our knowledge, this is the first time, a deep learning-based method is dedicated to handle nighttime defogging problem. To achieve our goal, we design grayscale and color modules, which rely mainly on the high/low frequency layers to enhance textures and at the same time suppress glow, fog and noise. Due to the lack of paired real ground-truths, our training process employs both paired synthetic data and unpaired real data. For this, we introduce new consistency losses between the outputs of the grayscale and color modules. Experimental results and evaluations, both quantitative and qualitative, show the effectiveness of our method.