Translation from RGB to SWIR Images for Adaptation of Detection and Semantic Segmentation Algorithms

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Outline

What is SWIR?

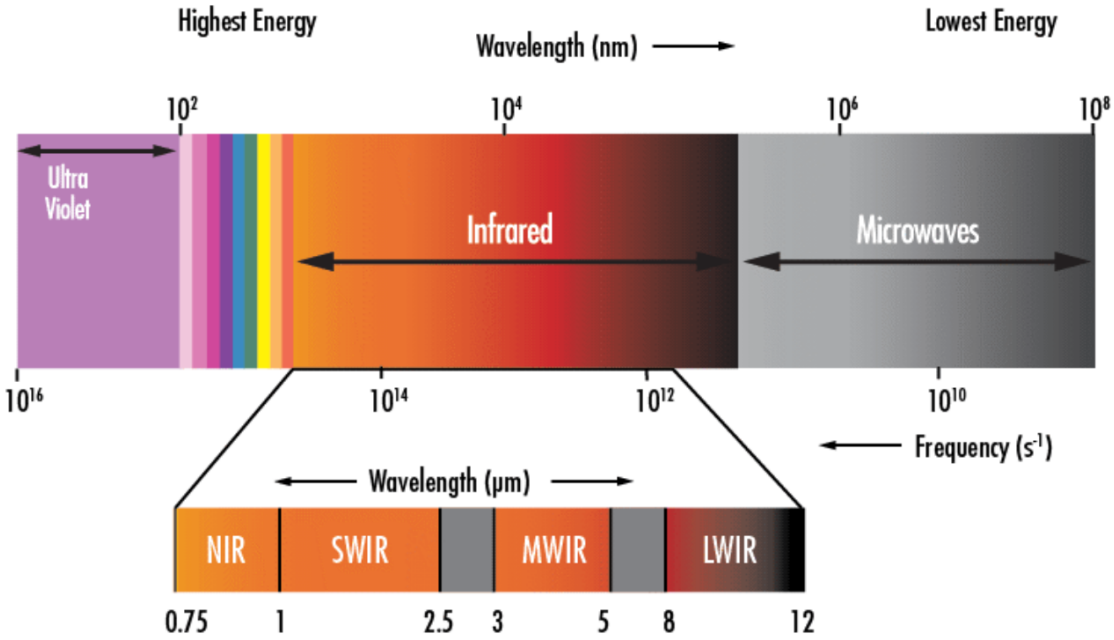
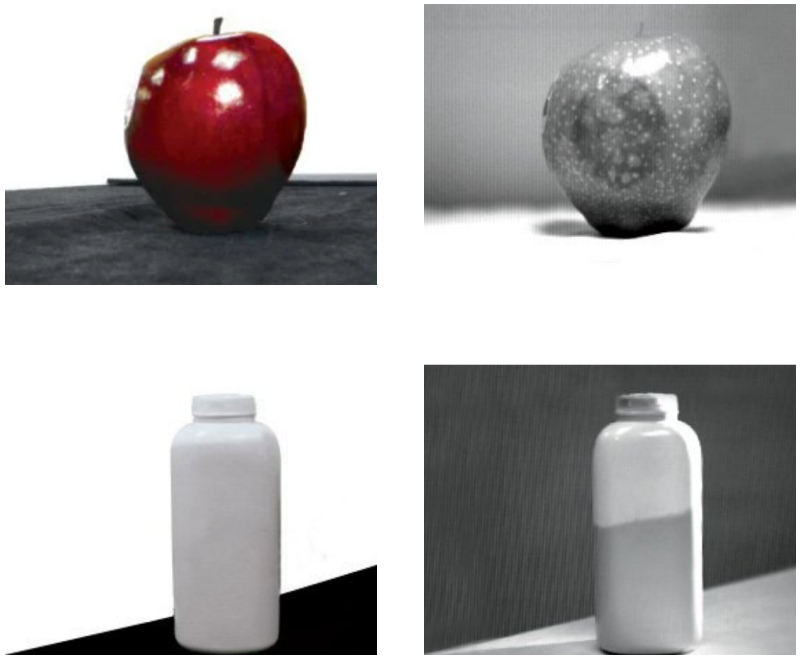


Figure: SWIR in Electromagnetic Spectrum

- Typically defined as light in the 0.9 – 1.7μm wavelength range, but can also be classified from 0.7 – 2.5μm.

Why Short-Wave Infrared?



(a) Visible Images (b) SWIR Images

Figure: Comparison between visible (left) and SWIR images (right).

- Atmospheric penetration (fog, rain, etc) and vision in low light (if presence of external radiation, e.g. moon, SWIR lighting, etc.)
- Improved contrast (plastic, liquid, paint, etc.)

Previous work

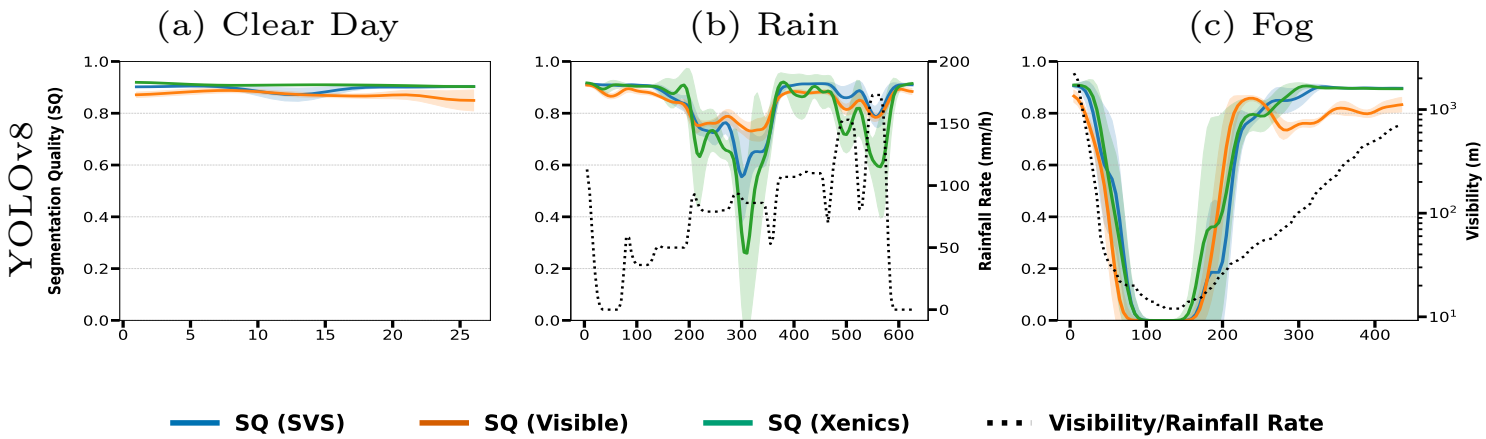


Figure: Segmentation Quality (SQ) as a function of time (with visibility/rainfall rate axis) comparing sensing modalities under different weather.

Previously: Applied RGB pre-trained object detection and segmentation models to SWIR driving images acquired in controlled weather conditions and compared results to corresponding visible-spectrum images.

Work accepted at ICCV Workshop 2025!

More at:

- rohmeh.github.io/docs/2024-SWIR-Project.pdf
- rohmeh.github.io/docs/2025-SWIR-IP-1-1.pdf

Objective and Procedure

Aim: Train models to translate RGB images into SWIR images in order to create a fake SWIR dataset fine-tune object detection models.

Procedure:

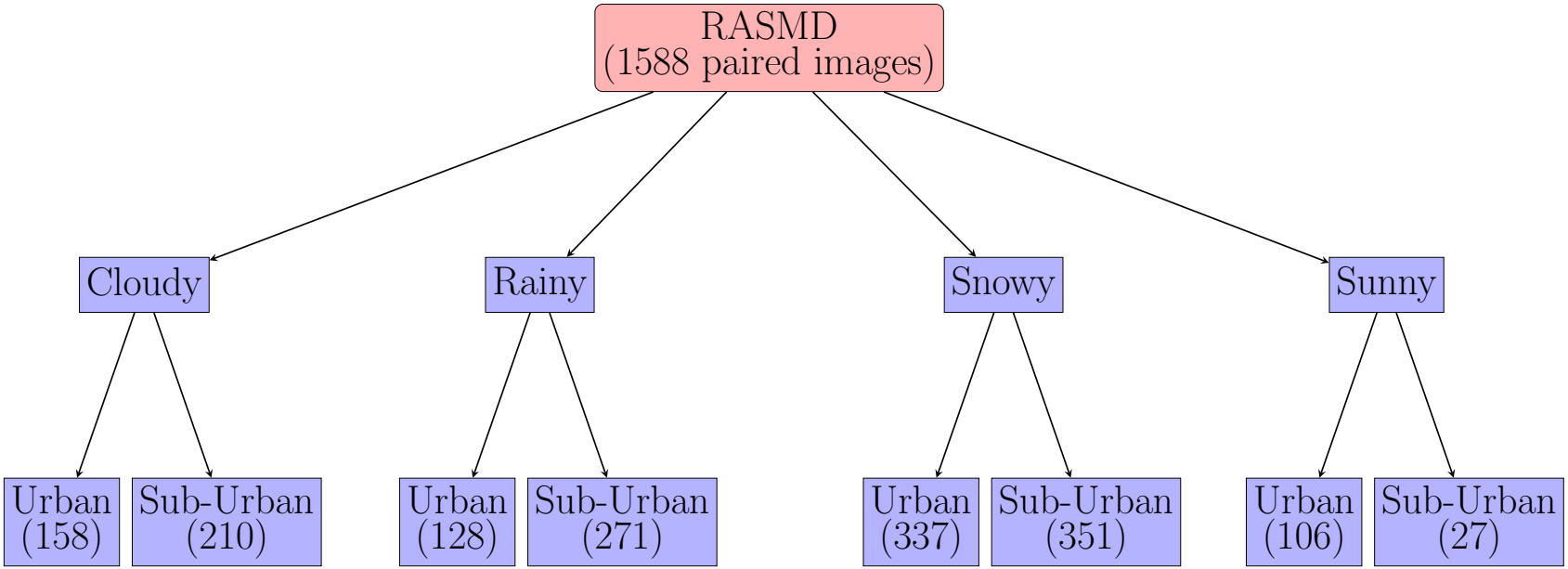
- Create dataset as part of RASMD [6] and split it into train/test/val.
- Train various models on the dataset.
- Evaluate on various traditional/learned-based metrics.

Dataset Used

RASMD (RGB And SWIR Multispectral Driving) [6]

- Comprises of **100,000 synchronized and pixel-aligned RGB-SWIR image pairs** collected across diverse urban and suburban locations, lighting, and weather conditions (sunny, cloudy, rainy, snowy).
- Data was acquired using a vehicle-mounted platform equipped with RGB [9] and SWIR cameras [8], covering **163.3 km over 8.5 hours** of driving.
- The dataset includes annotations for object detection (6 traffic-related classes).

Training Dataset Created



- **Dataset Split: 1588 total (Paired)**
  - Training: 1111 images (70%)
  - Validation: 238 images (15%)
  - Testing: 239 images (15%)

Sample Images

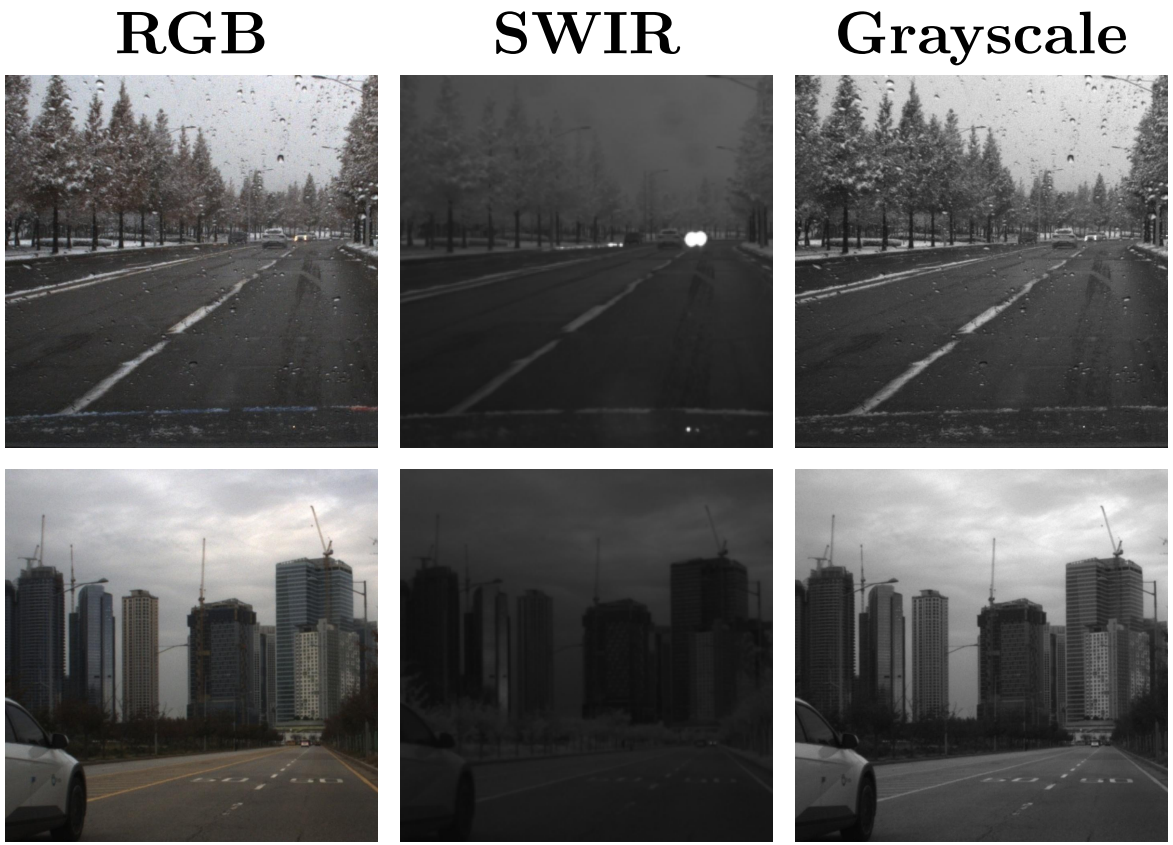


Figure: Images from RASMD [6] dataset and corresponding grayscale converted images for comparison.

Models used for translation

Model	Type	Paired/Unpaired
CUT [13]	GAN	Unpaired
FastCUT [13]	GAN	Unpaired
CycleGAN [12]	GAN	Unpaired
Pix2Pix [10]	GAN	Paired
Pix2PixHD [11]	GAN	Paired
BBDM [14]	Diffusion	Paired

- 6 Model were used - 1 diffusion based paired translation, 2 GAN based paired translation, and 3 GAN based unpaired translation models.

Pix2Pix: Conditional GANs for Paired Translation [10]

Idea:

- Designed for **paired image-to-image translation**.
- Learns a mapping from input image to output using conditional GANs.
- Uses a U-Net generator for spatial correspondence.

Loss Functions:

- **Adversarial loss:** makes output indistinguishable from real target images.
- **L1 loss:** encourages the output to be close to ground-truth in pixel space.

Pix2PixHD: High-Resolution Paired Translation [11]

Idea:

- Extension of Pix2Pix for **high-resolution** and **photo-realistic** image synthesis.
- Incorporates multi-scale discriminators and a coarse-to-fine generator.

Loss Functions:

- Adversarial loss: at multiple scales for better detail.
- Feature matching loss: stabilizes GAN training by matching intermediate discriminator features.
- Perceptual loss: improves visual quality and realism.

CycleGAN: Cycle-Consistent Adversarial Networks [12]

Idea:

- Enables **unpaired, bidirectional** image-to-image translation.
- Learns mappings between two domains using the concept of *cycle-consistency* where it ensures that translating from one domain to another and back yields the original image.

Loss Functions:

- **Adversarial loss:** ensures generated images resemble the target domain.
- **Cycle-consistency loss:** enforces that $x \to G(x) \to F(G(x)) \approx x$ and $y \to F(y) \to G(F(y)) \approx y$.
- Identity loss: preserves color composition and stabilizes training.

CUT: Contrastive Unpaired Translation [13]

Idea:

- Enables **unpaired, one-sided** image-to-image translation.
- Preserves input content by maximizing mutual information between **local patches** in input and output.
- Uses a **shared latent space** to align features from corresponding patches.

Loss Functions:

- **Adversarial loss:** ensures generated images resemble the target domain.
- **PatchNCE loss:** contrastive loss that aligns corresponding patches in input and output using negative sampling.
- **Identity loss:** regularizes training by discouraging unnecessary changes to domain B inputs.

Architecture:

- Encoder-decoder generator with multi-layer feature extraction.
- No backward generator or cycle consistency.

FastCUT [13]

Idea:

- A **lighter and faster variant** of CUT.
- Trades output quality for significantly reduced computational cost.

Loss Functions:

- Adversarial loss: ensures generated images resemble the target domain.
- PatchNCE loss: contrastive loss between input and output patches.
- *No identity loss*

Comparison to CUT:

- Removes identity loss and adjusts regularization ($\lambda_X = 10$, $\lambda_Y = 0$).

BBDM: Brownian Bridge Diffusion Model [14]

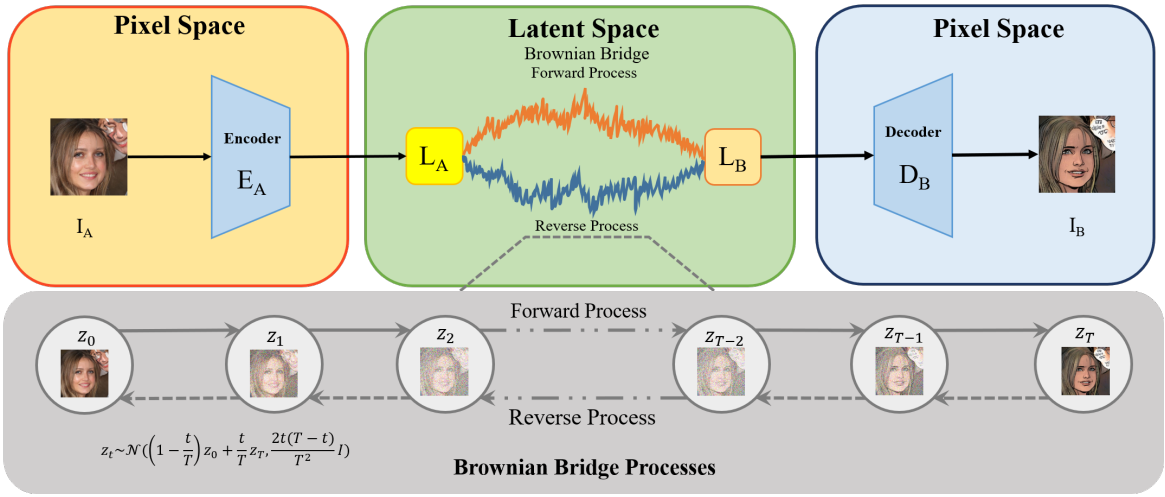


Figure: BBDM Architecture

Idea:

- Uses **diffusion models** for paired image-to-image translation.
- Models the translation as a conditional diffusion process guided by a Brownian bridge.

Loss Functions:

- Diffusion loss: score-matching loss to denoise at each step.
- Conditioning on the input ensures the diffusion path leads to the desired output.

Evaluation Metrics

Paired Data Metrics:

- **PSNR** ↑: Pixel-level fidelity (logarithmic, dB scale)
  - $\text{PSNR} = 10 \log_{10} \left(\frac{\text{MAX}_I^2}{\text{MSE}} \right)$
- **SSIM** ↑: Structural similarity (0 to 1)
  - Combines luminance, contrast, and structure comparisons
- **RMSE** ↓: Root Mean Square Error
  - $\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$

Learned Metrics:

- **FID** ↓: Fréchet Inception Distance
  - Compares feature distributions in Inception-v3 space
- **LPIPS** ↓: Learned Perceptual Image Patch Similarity
  - Uses deep network features to match human perception

Implementation Details

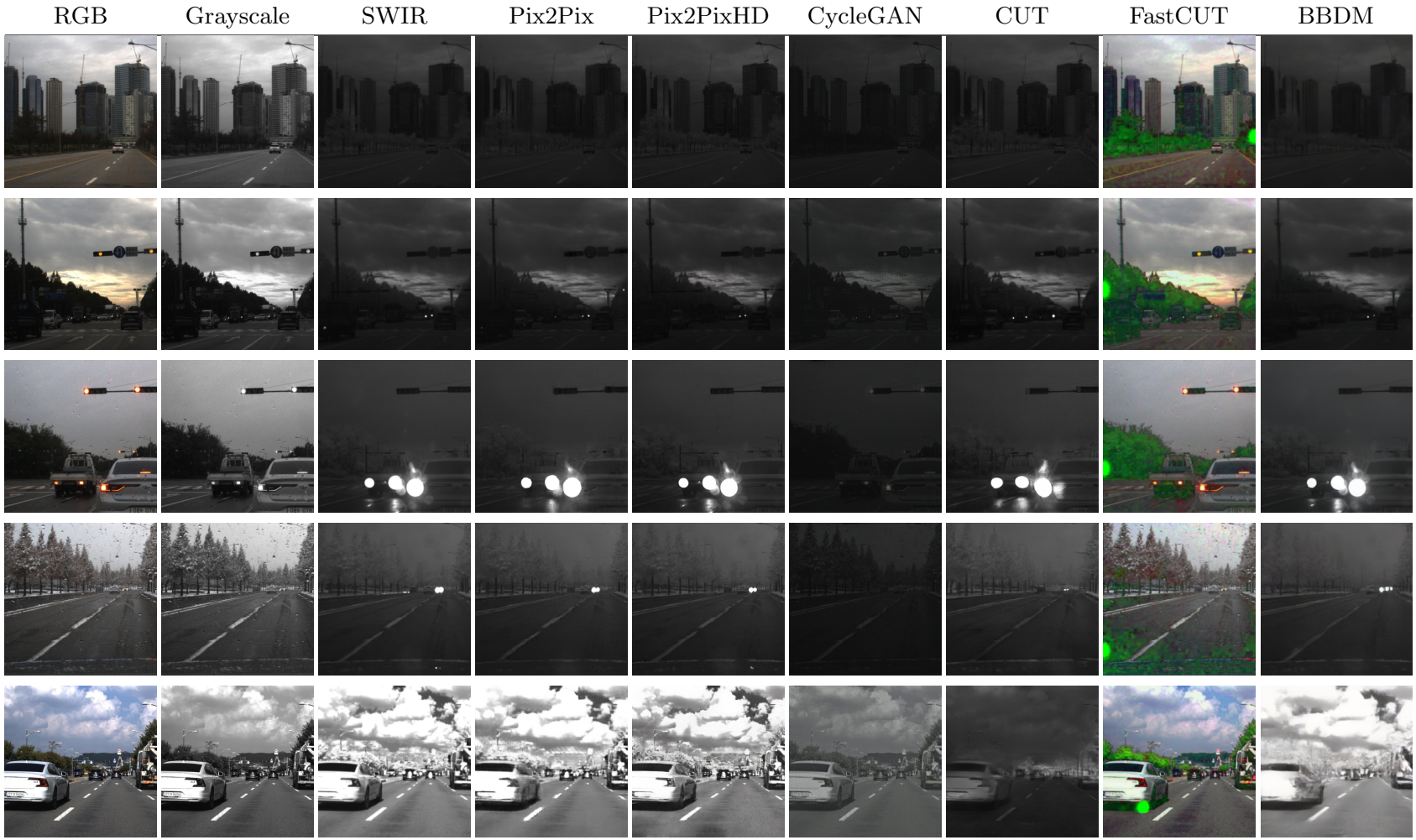
Hardware:

- GPU: NVIDIA GeForce RTX 2080
- VRAM: 8GB
- Driver: 570.124.06
- CUDA: 12.8

Software:

- OS: Ubuntu 22.04 LTS
- PyTorch (CUDA 12.5)
- torchvision

Visual Results



Quantitative Results

Method	**Type**	**PSNR ↑**	**SSIM ↑**	**RMSE ↓**	**FID ↓**	**LPIPS ↓**
Pix2Pix [10]	GAN	<u>33.2341</u>	<u>0.9190</u>	<u>7.3704</u>	67.4492	<u>0.0679</u>
Pix2PixHD [11]	GAN	**34.4085**	**0.9345**	**6.6343**	**38.6485**	**0.0413**
CycleGAN [12]	GAN	21.0338	0.7457	28.7373	94.8574	0.1803
CUT [13]	GAN	26.3492	0.8049	26.3492	<u>56.3365</u>	0.1348
FastCUT [13]	GAN	10.4322	0.3802	79.5787	157.0999	0.4743
BBDM [14]	Diffusion	32.1020	0.9040	8.2781	66.1329	0.0804

Table: Quantitative comparison of different methods using image quality metrics. Higher values are better for PSNR and SSIM; lower values are better for RMSE, FID, and LPIPS.

Conclusion

- Pix2PixHD gives the best performance overall, where Pix2Pix and BBDM also give comparative scores. All of these are paired image translation methods.
- CycleGAN and CUT achieve similar scores, lower compared to unpaired translation models.
- FastCUT struggles to adapt to the SWIR domain, and produces identifiable images.

Relative Order:

Pix2Pix > Pix2Pix > BBDM >> CUT > CycleGAN >> FastCUT

Limitations and Future Works

Limitations:

- The dataset used for training has driving sequence-based images and may overfit the models.
- The images are not homographically aligned well as provided in [6] which may affect performce as well as training of models.

Future Works:

- Translate a full-fledged RGB dataset to SWIR.
- Train metric to evaluate quality of SWIR images.
- Re-train the Detection and Semantic Segmentation Algorithms on the dataset.
- Compare the performance with the results of visible pre-trained algorithms.

Questions and Reviews

Any Questions?
Reviews Please!

Merci! Thank You! धन्यवाद شكريه

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