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EGU General Assembly 2025

Mining for tomorrow: from technological advances in exploration and production to sustainable post-mining solutions

UTLD: An Underground Thermal and LiDAR Dataset for Depth Estimation

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Background and Motivation

- Recently, global mining industries have been accelerating their transformation towards intelligence, with the developments of 5G communication, automated equipment, and digital twin techniques.
- For mining intelligence, one of the basic tasks is to achieve the 3D maps of mining space with applications, i.e., virtual reality, self-driving, remote excavation, emergency rescue, etc.

Virtual Reality

Self Driving

Remote Excavation

Robot Emergency Rescue

Background and Motivation

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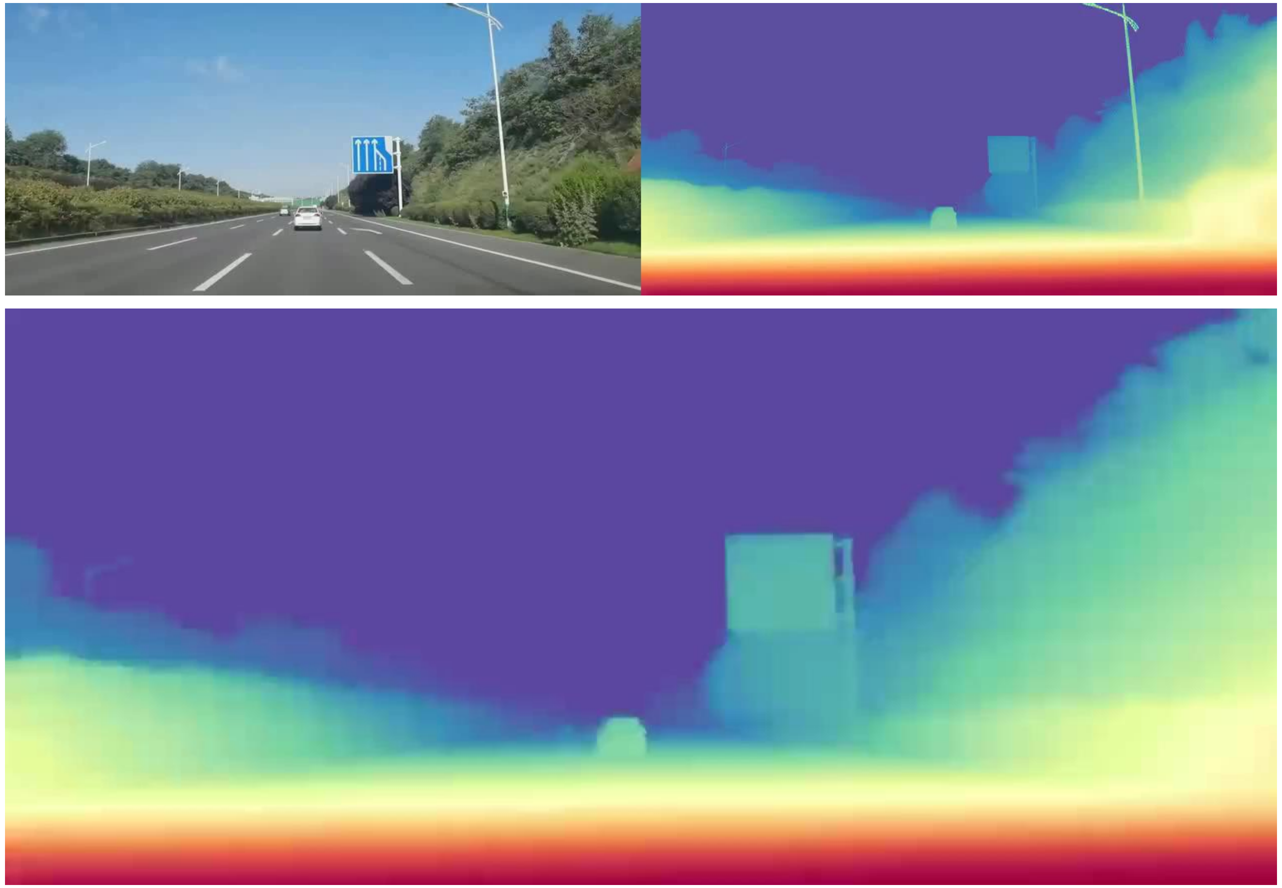
◆ Techniques for 3D mapping

LiDAR Technique

- Straightforward;
- Lighting independent.

Depth Estimation



- Visual-based;
- Lighting affected.

Background and Motivation

◆ Specific Mining Activity

Tunnel Excavation

RGB video

Thermal Video

- Limited access to visual information
- Unable to adapt to the underground environment
- Low robustness to dust condition

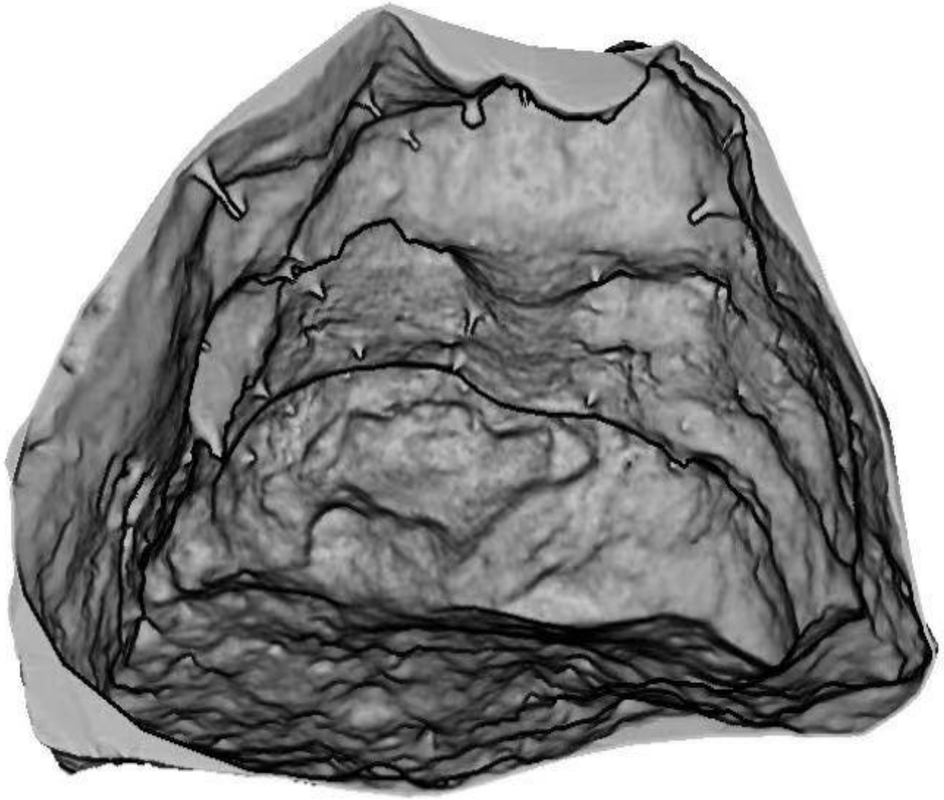
- Insensitive to illumination conditions
- Adaptable to underground environments
- High robustness to dust condition

Background and Motivation

◆ Specific Mining Activity

Tunnel Excavation

➢ **In-site testing for LiDAR data**



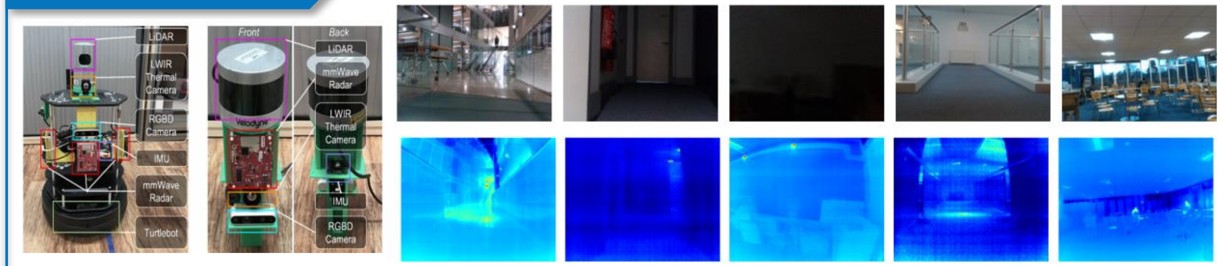
- **Highly sensitive to dust conditions**

No data!

when the dust ratio is high

Background and Motivation

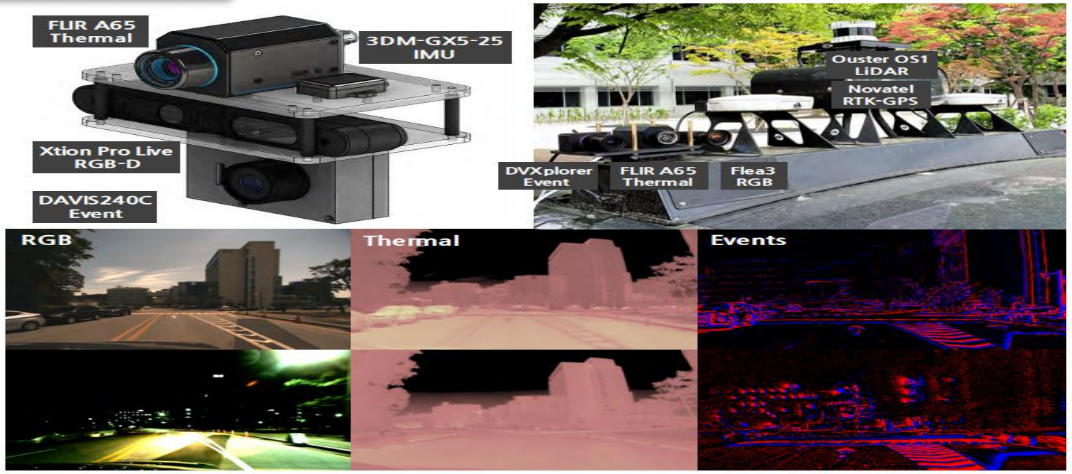
INDOOR



Source: Li P., Cai K., Saputra M. R. U., et al., “OdomBeyondVision: An Indoor Multi-modal Multi-platform Odometry Dataset Beyond the Visible Spectrum,” in 2022 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2022, pp. 3845–3850.

DataSet	Year	Scene	Condition	Lidar	Thermal	
					Mono	Stereo
CATS	2017	In/Outdoor	Day/Night	√	√	√
KAIST	2018	Outdoor	Day/Night	√	√	×
ViViD	2019	In/Outdoor	Day/Night	√	√	×
MultiSpectralMotion	2021	In/Outdoor	Day/Night	√	√	×
ViViD++	2022	Outdoor	Day/Night	√	√	×
OdomBeyond Vision	2022	Indoor	Day/Night	√	√	×
MS^2	2023	Outdoor	Day/Night/Rain	√	√	√
NTU4DRadLM	2023	Outdoor	Day	√	√	×
ZJU-Multispectrum Dataset	2024	Outdoor	Day/Night/Dust	√	√	×
Ours	2025	Underground	Low light/Dust	√	√	√

OUTDOOR



Source: Lee, Alex Junho, et al. "Vivid++: Vision for visibility dataset." IEEE Robotics and Automation Letters 7.3 (2022): 6282-6289.

Problems

- Low light, high dust, and complex geometry disrupt data capture by conventional vision sensors and LiDAR.
- Most depth estimation datasets focus on indoor/outdoor scenes, limiting research and practical applications in underground mines.

Lack of datasets for underground scenes

Dataset Overview

◆ Data Acquisition Platform

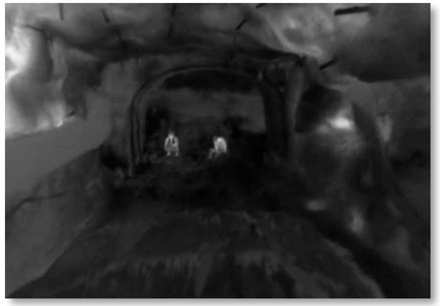
- **Remotely controlled robot**
- **Thermal camera and Laser scanner sensors in stereo configuration**

Dataset Overview

◆ Study Areas

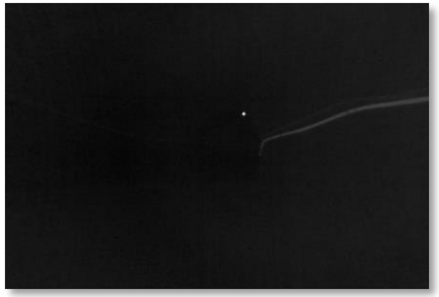
✓ Coal mine

- **Depth**: -800 m
- **Scene elements**: excavation face, tunnels, vehicles…



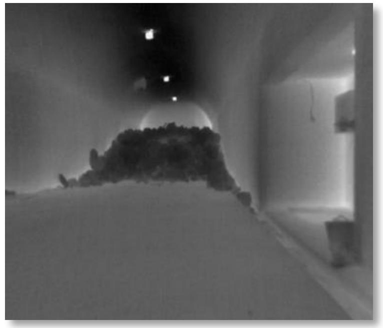
✓ Metal mine

- **Depth**: -325 m
- **Scene elements**: Tunnel, person, vehicles…



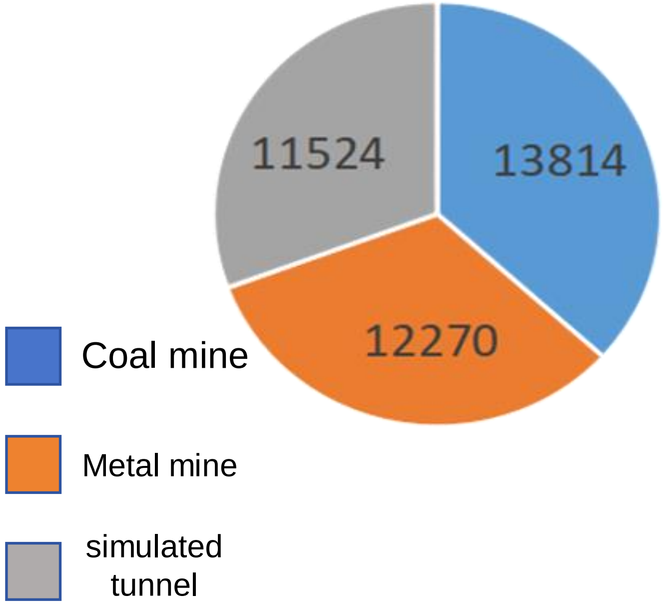
✓ Simulated tunnel

- **Depth**: -10 m
- **Scene elements**: Excavation face, person, vehicles…



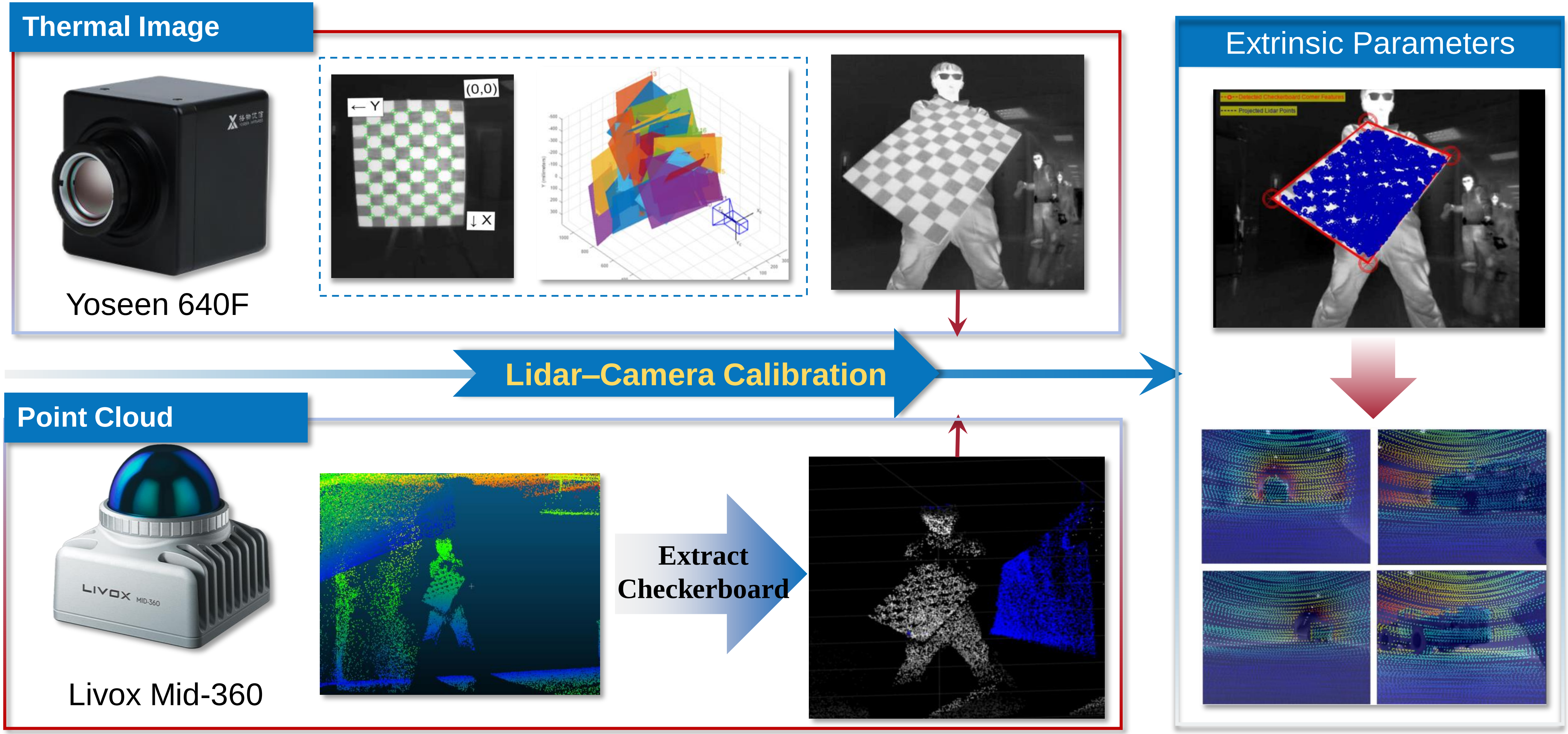
Dataset statistics

The UTLD dataset comprises 13,814 coal-mine images, 12,270 metal-mine images, and 11,524 simulated-tunnel images, for a total of 37,608 images.



Dataset Overview

◆ Sensor Calibration



Benchmarking Depth Estimation Methods

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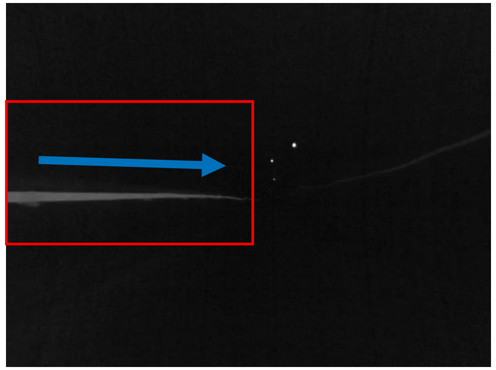
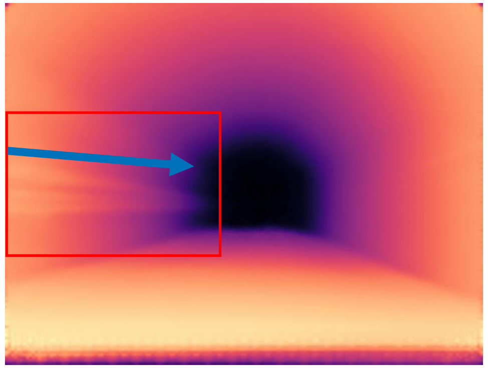
◆ Quantitative Evaluation

- Eight classic Monocular depth estimation methods were used for Benchmarking the UTLD dataset.
- **Error increases with distance**
- **<15m:** Adabins best; **15–20m:** PixelFormer best in metal mine and simulated-tunnel; ＞ **20 m:** Transdepth and Adabins lead the results.
- **Error：** Simulated tunnel > Coal mine > **Metal mine**

  Due to its minimal temperature variation.





- **Average RMSE ranges from 0.1 m to 0.25 m (0-5m).**

Table1. Coal mine

Model	Type	0-5m	5-10m	10-15m
BTS	R	0.66	1.34	2.34
GLP	R	0.36	0.68	1.01
Transdepth	**R**	**0.26**	**0.55**	**1.01**
SwinV2-T	R	0.35	0.63	1.02
Newcrfs	R	0.26	0.5833	0.99
Adabins	**R+C**	**0.25**	**0.54**	0.97
IEbins	R+C	0.27	0.63	1.02
PixelFormer	R+C	0.25	0.57	0.96

Table2. Metal mine

Model	Type	0-5m	5-10m	10-15m	15-20m	20+m
BTS	R	0.48	1.12	2.12	2.90	2.98
GLP	R	0.38	0.4994	0.75	0.95	1.67
Transdepth	R	0.14	0.28	0.60	**0.88**	**1.25**
SwinV2-T	R	0.37	0.47	0.7491	0.98	1.80
Newcrfs	R	**0.13**	**0.28**	**0.58**	0.92	1.65
Adabins	R+C	**0.12**	**0.26**	**0.56**	0.90	1.94
IEbins	R+C	0.15	0.3115	0.6051	0.89	1.65
PixelFormer	R+C	0.13	0.2809	0.5726	**0.83**	**1.35**

Table3. Simulated tunnel

Model	Type	0-5m	5-10m	10-15m	15-20m	20+m
BTS	R	0.32	0.82	1.64	3.01	4.79
GLP	R	0.30	0.74	1.72	2.21	3.14
Transdepth	**R**	**0.23**	**0.56**	**1.09**	**2.00**	**3.03**
SwinV2-T	R	0.35	0.72	1.18	2.00	3.08
Newcrfs	R	0.24	0.60	1.35	2.04	3.15
Adabins	R+C	**0.21**	0.60	**1.08**	1.98	**2.98**
IEbins	R+C	0.24	0.71	1.30	2.19	3.14
PixelFormer	R+C	0.24	**0.59**	1.10	**1.96**	3.02

Benchmarking Depth Estimation Methods

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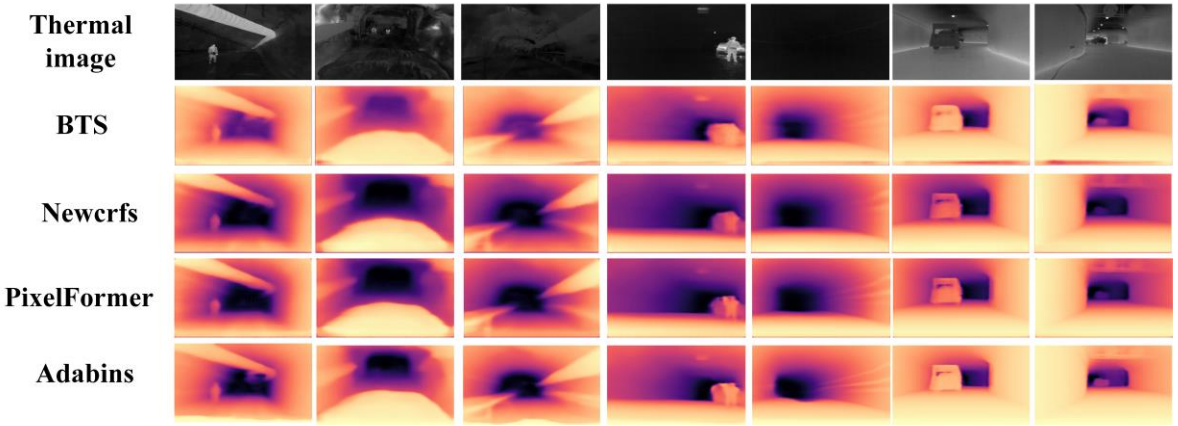
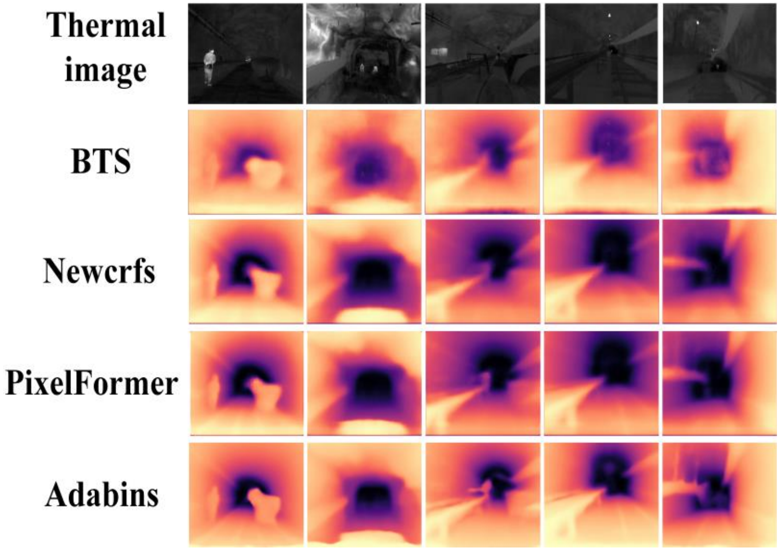
◆ Qualitative Evaluation

- ➢ **Reasonably captures the scene's overall geometry**
- ➢ **Struggles to estimate depth for moving objects**
- ➢ **Blurred boundaries**

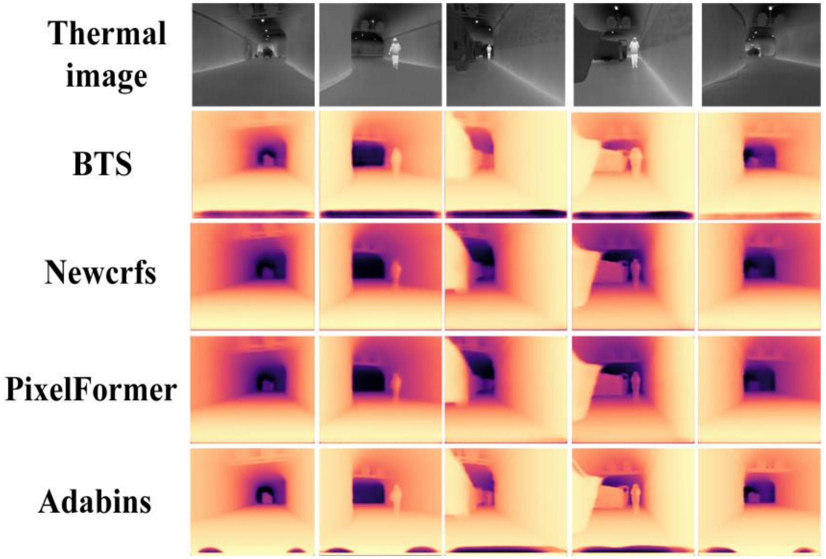
✓ Mix scenes



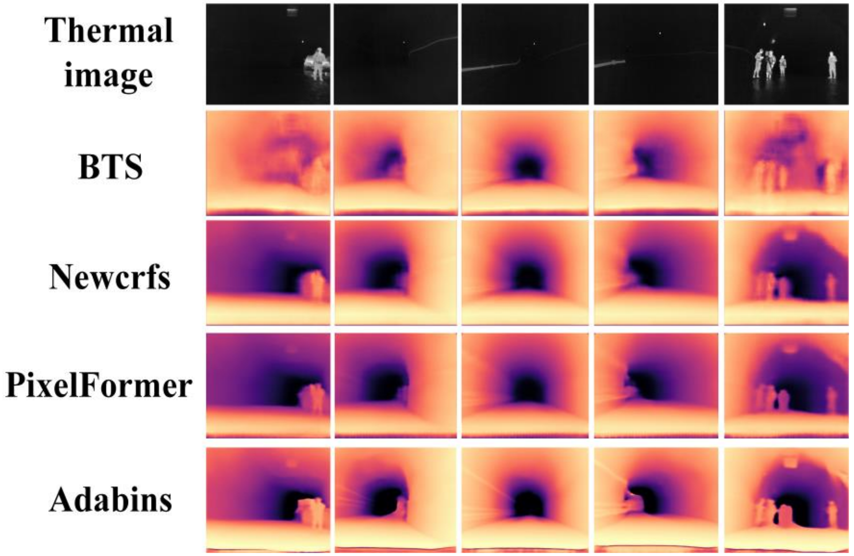
✓ Coal mine



✓ Metal mine



✓ Simulated tunnel



Benchmarking Depth Estimation Methods

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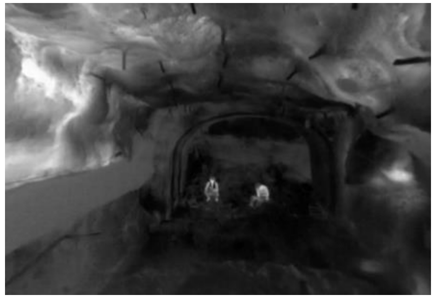
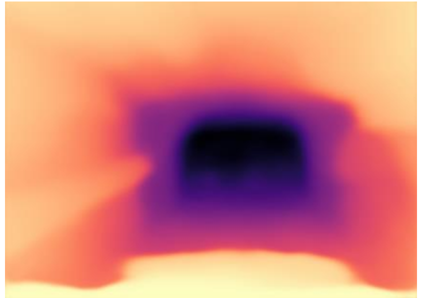
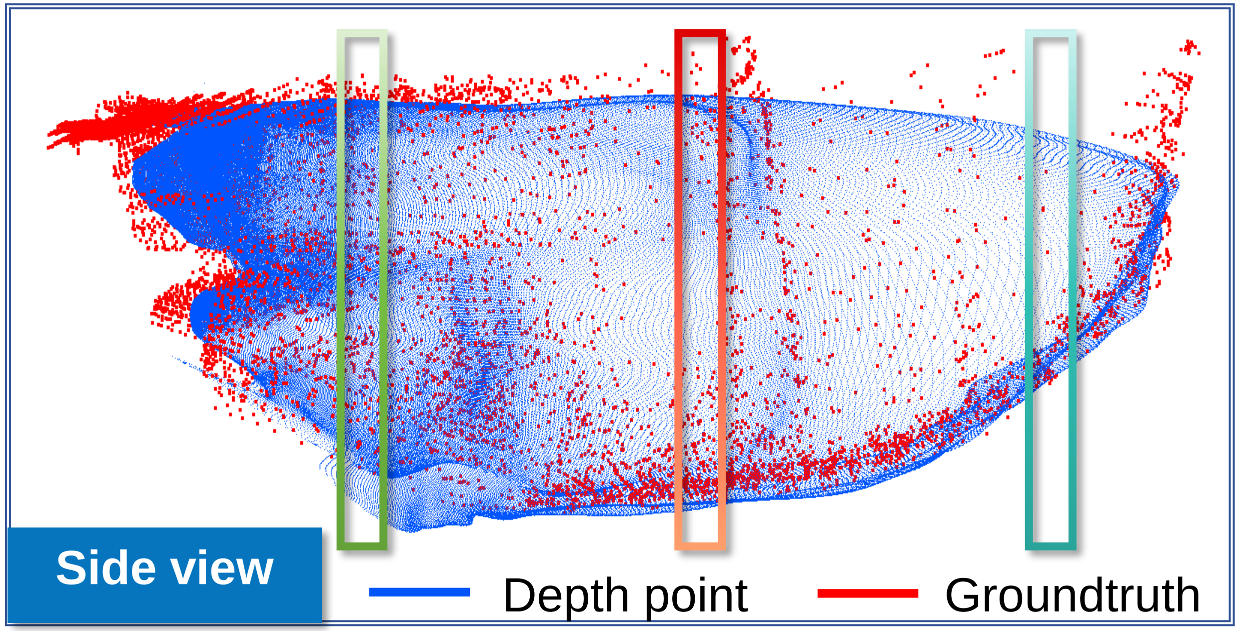
◆ Cross-Sectional Analysis



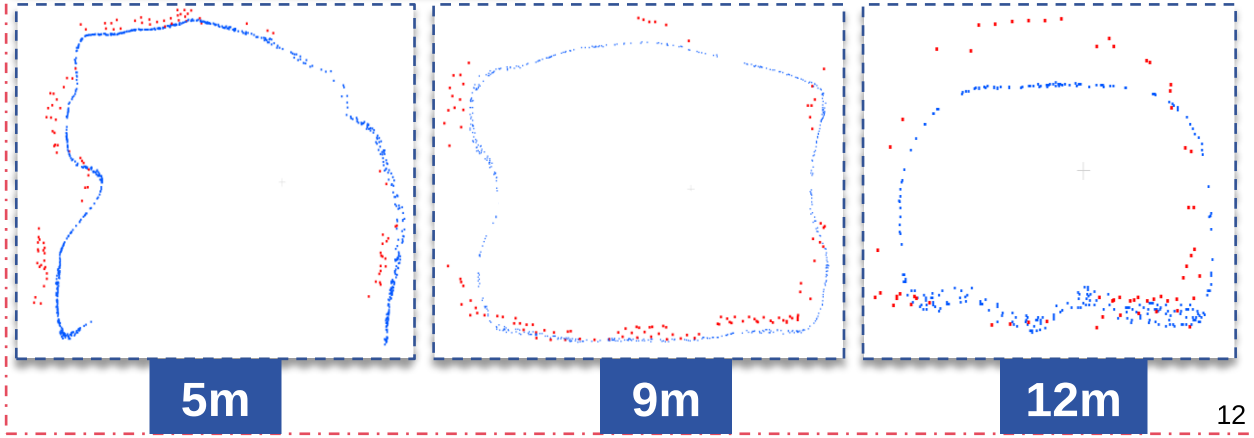
Thermal image



Depth image



Cross-section

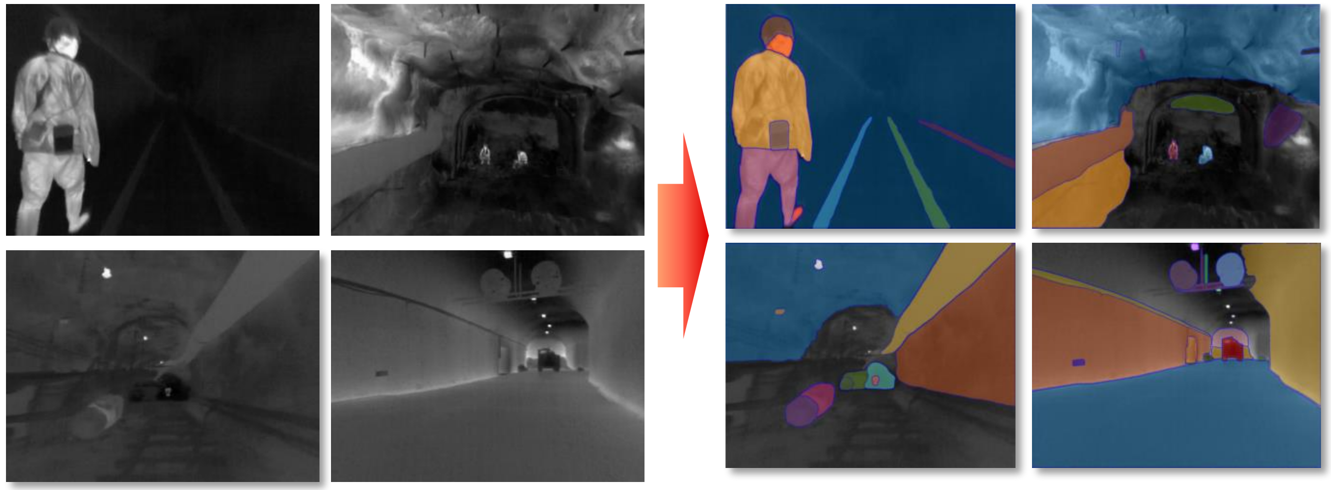


Challenges & Opportunities

◆ Future work

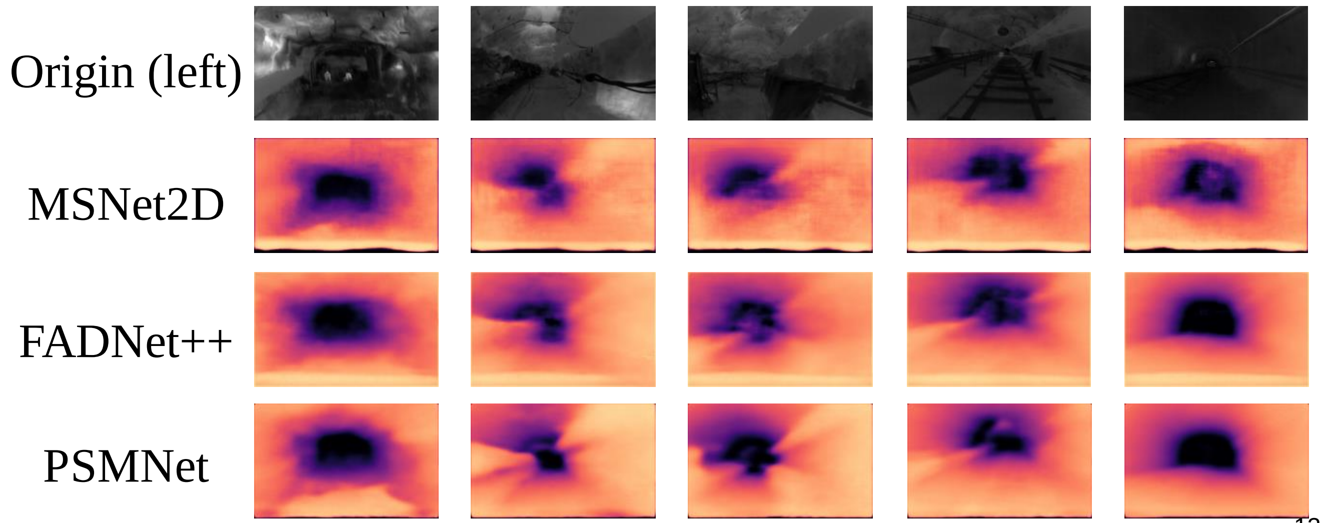
- ➢ Real-time segmentation
- ➢ Multi-modal fusion (LiDAR + thermal)
- ➢ Domain adaptation to diverse mining activities

Semantic-guided underground depth estimation



☐ **Binocular** Thermal image Depth Estimation

- ➢ Semantic guided stereo matching
- ➢ Stereo matching in low-texture scenes
- ➢ Stereo matching in low-contrast scenes



Challenges & Opportunities

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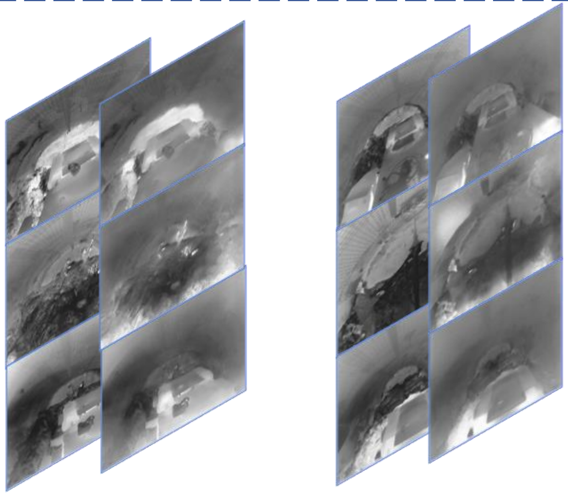
Dust Thermal Dataset For Mine Excavation Faces

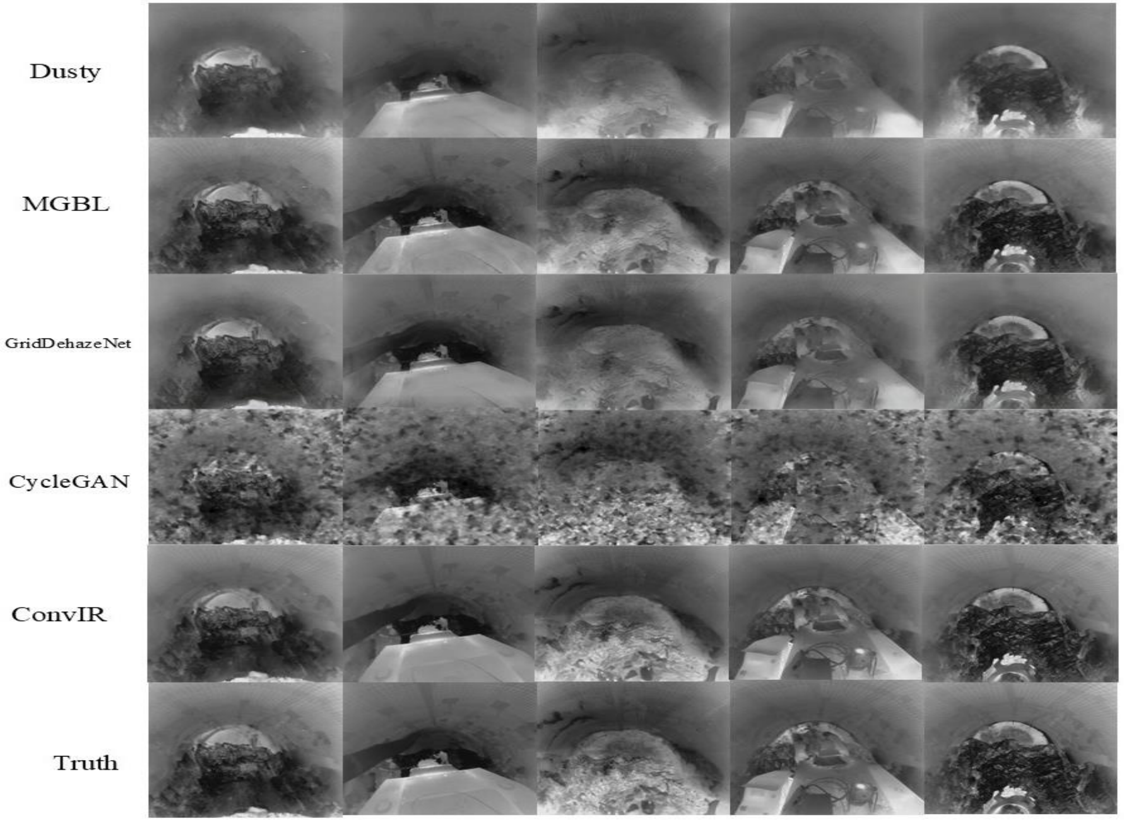
◆ Image quality improvement

We assembled a thermal image dataset comprising both **real and synthetic** thermal images under **dusty** and **clear** conditions.



Fundamental parameters		Numerical value
Dataset_name		TF-Dust
Optical response band		8–14μm
Image_size		720*720
Images	authentic	100 pairs
	synthetic	10000 pairs
Temperature measurement range		-20℃-150℃

Dust-Removeal Algorithm test



Metric/methods	CycleGAN	GridDehazeNet	MGBL	ConvIR
PSNR_AVR	18.969	23.494	28.935	33.84
SSIM_AVR	0.658	0.868	0.896	0.964
Runtime_AVR	0.606	0.712	0.033	0.10

Our Team

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Thank you for your attention!

Questions are welcome

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