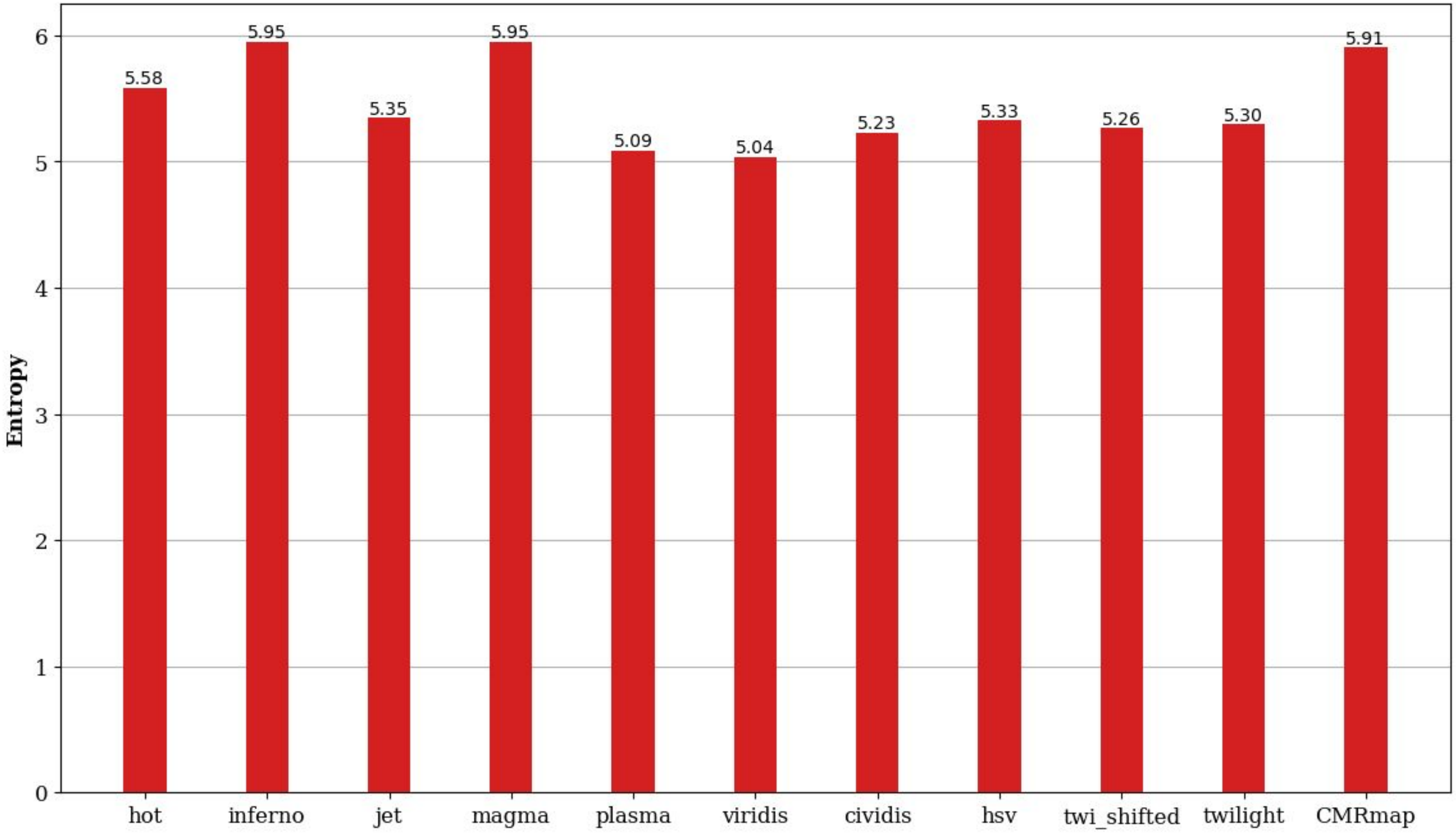
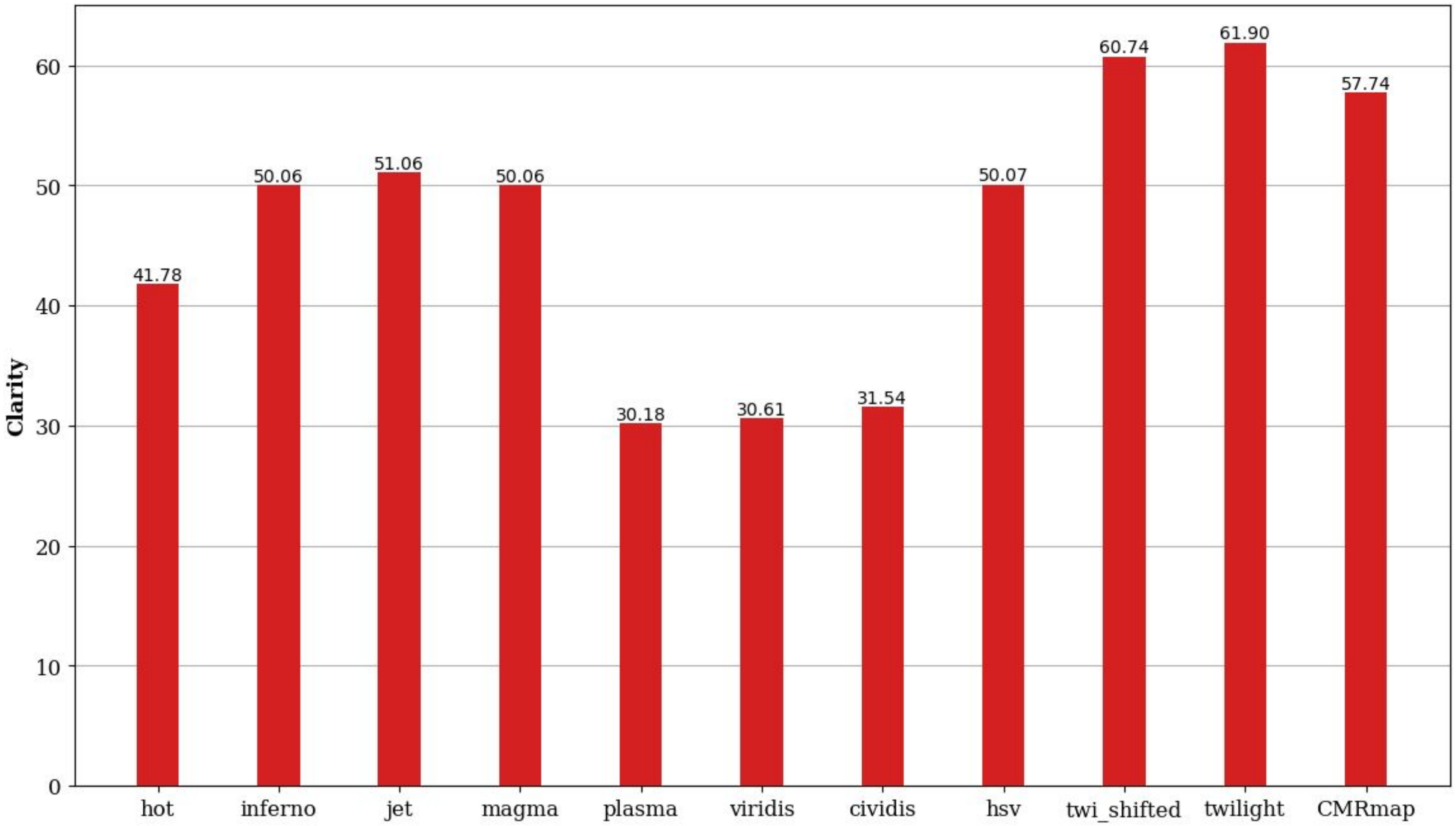
Meeting
02/07/2024

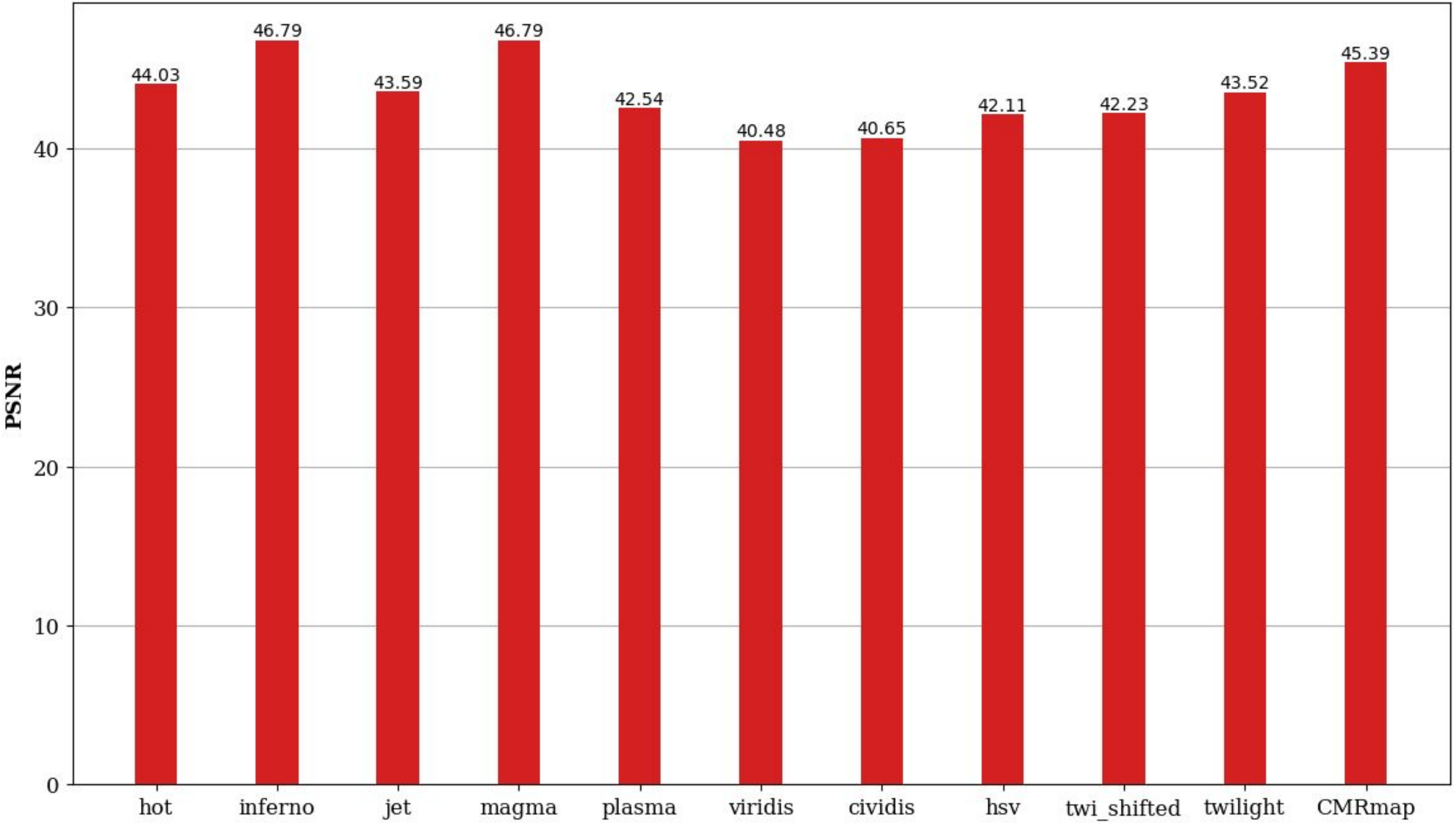
Focused Range: Entropy



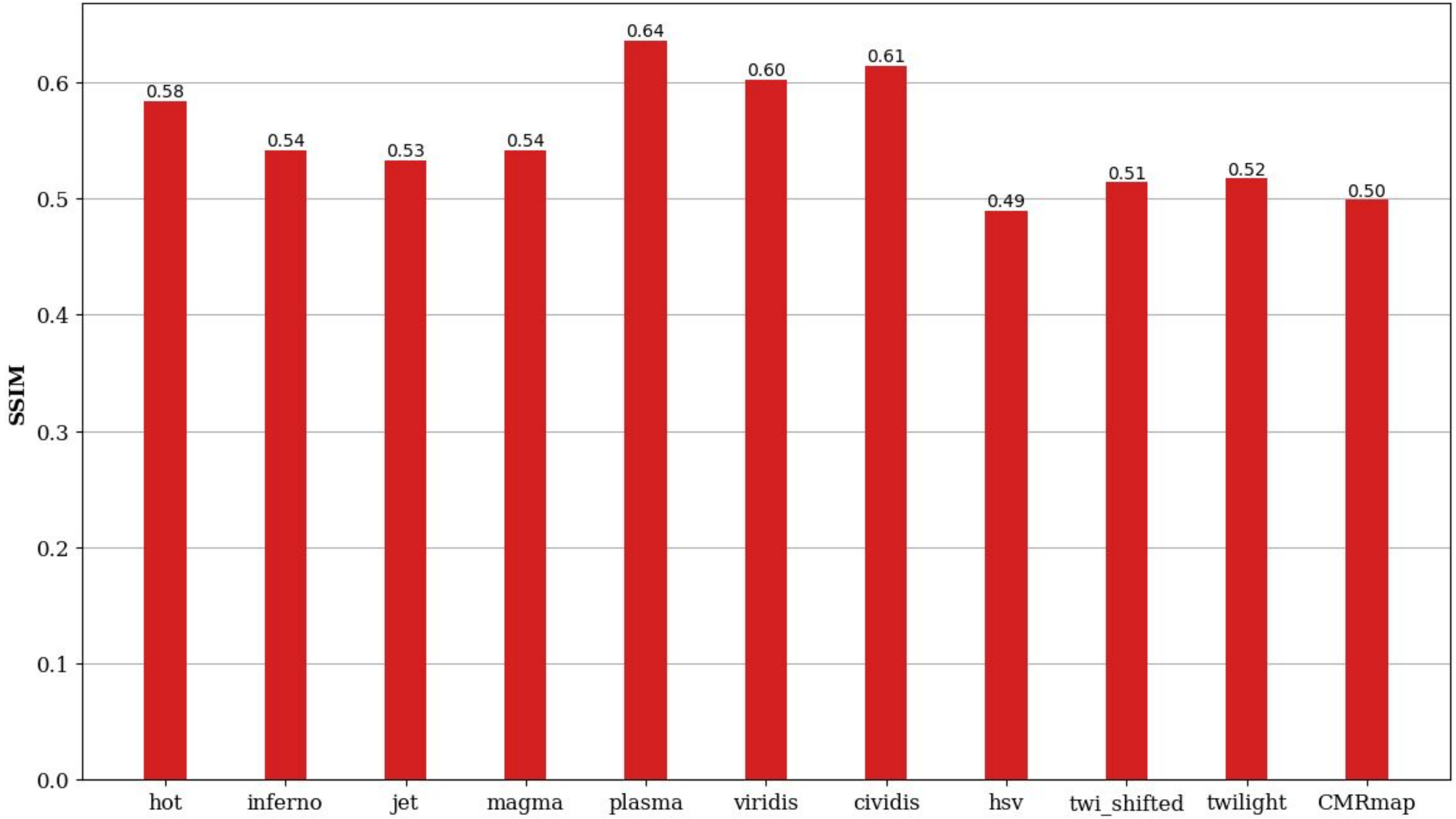
Focused Range: Clarity



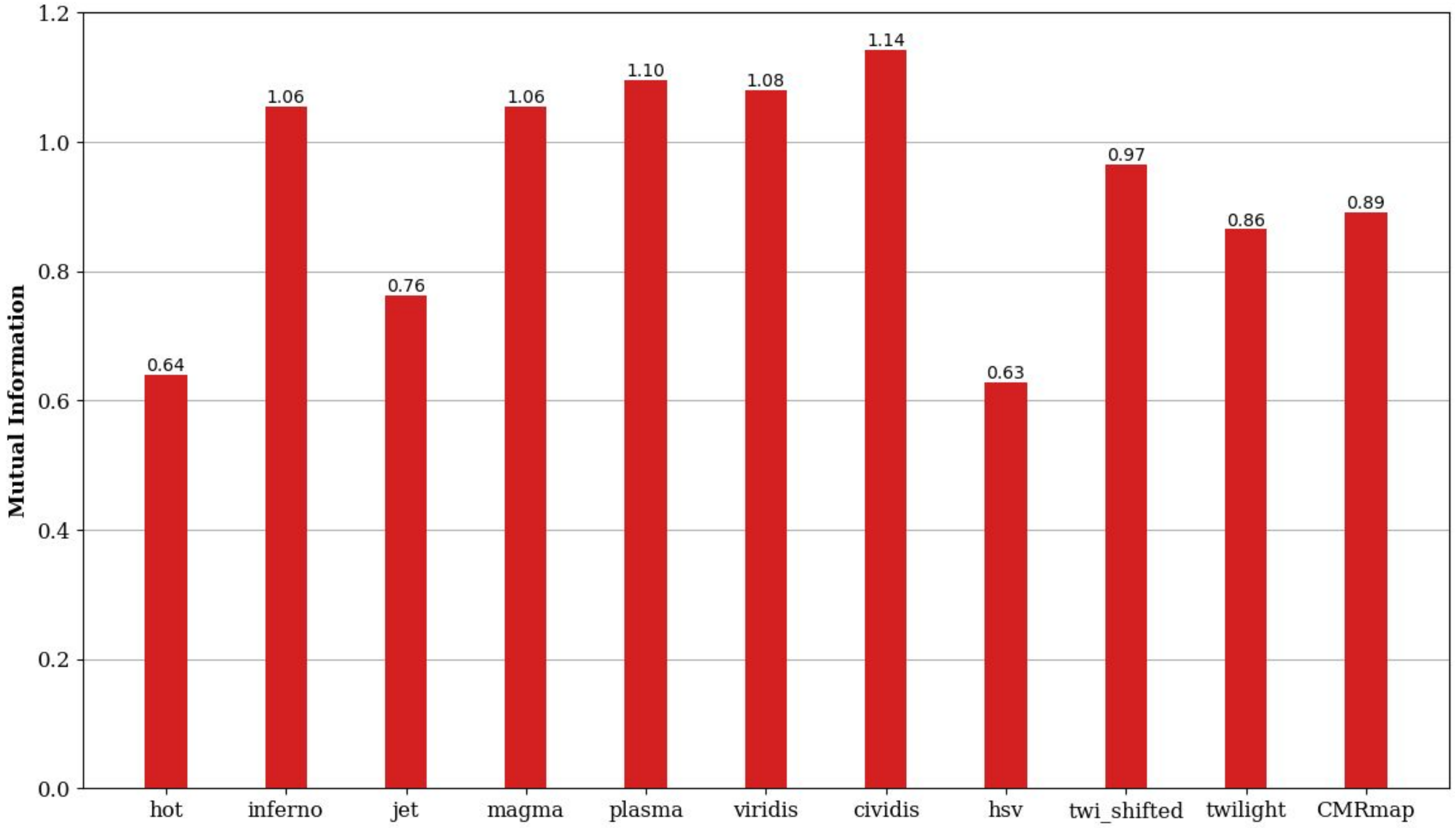
Focused Range: PSNR

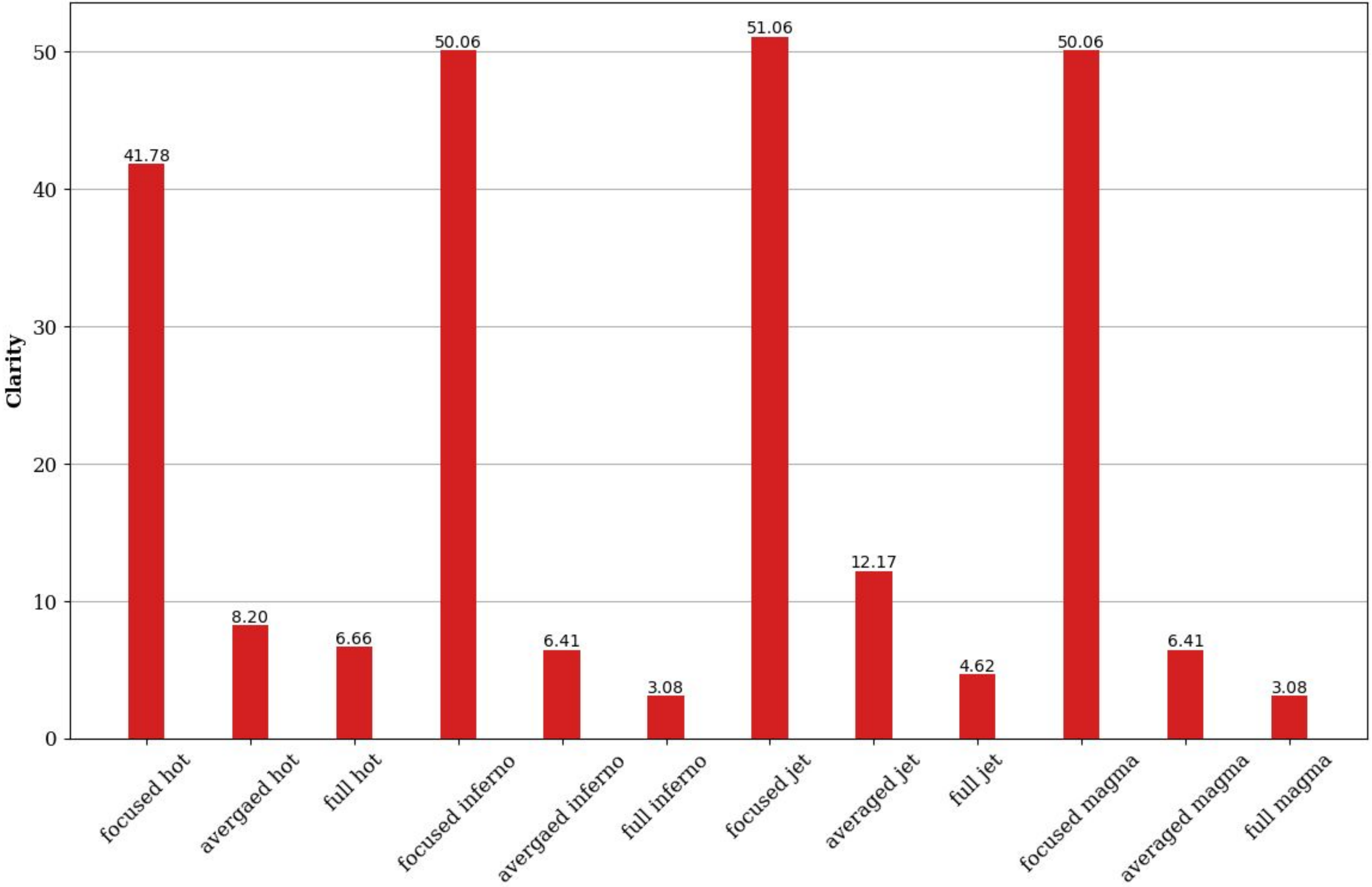


Focused Range: SSIM

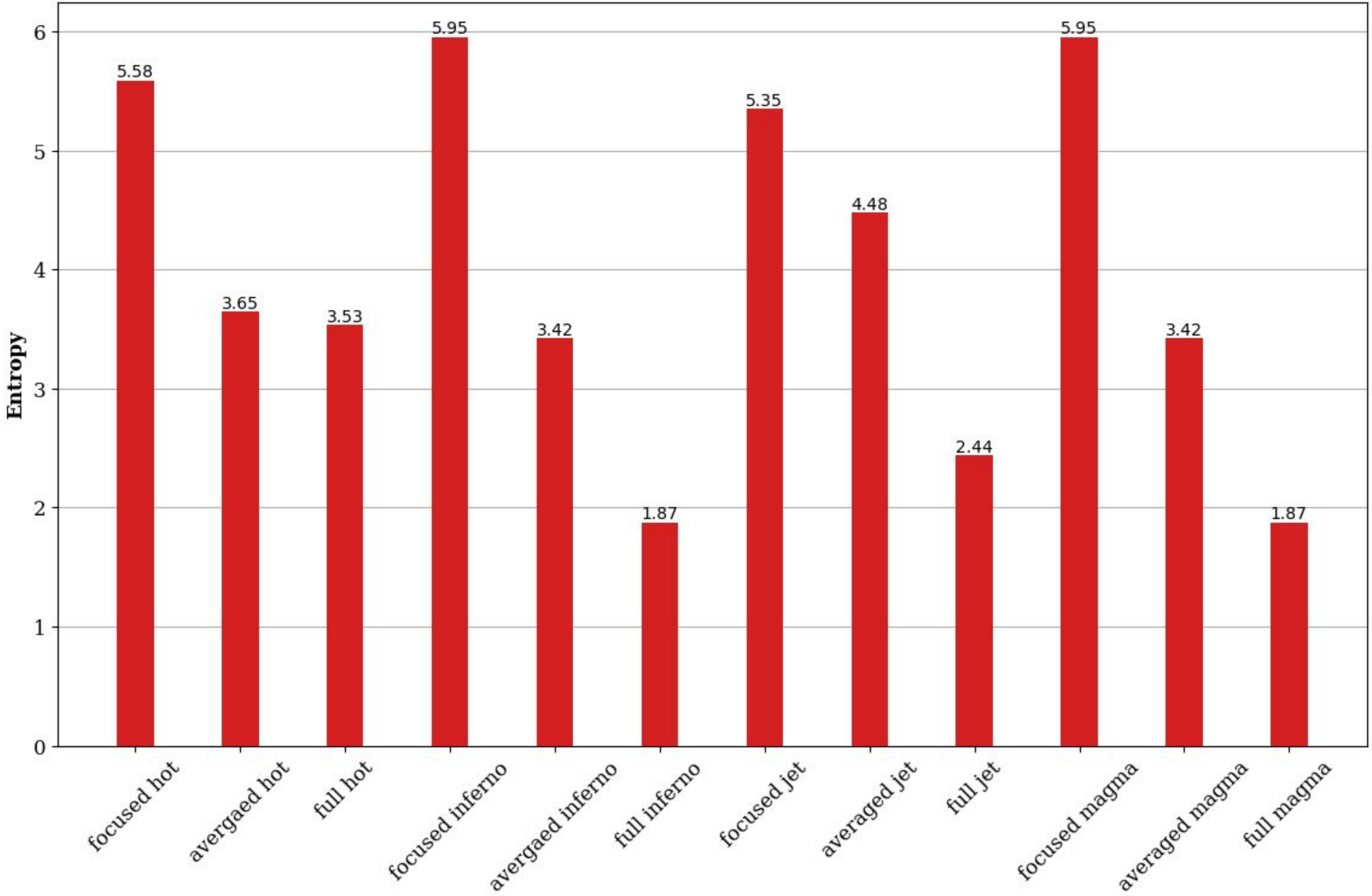


Focused Range: MI

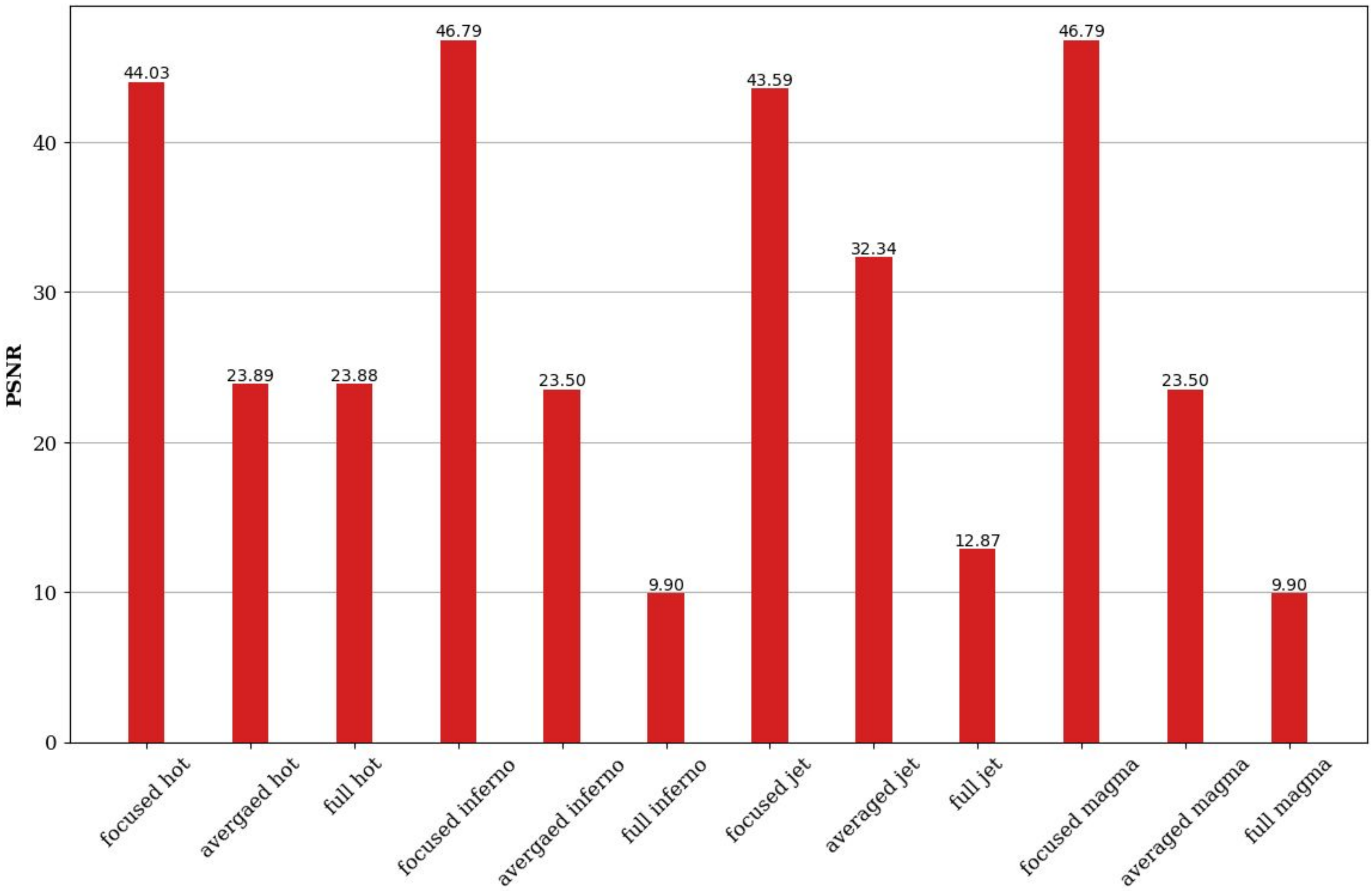


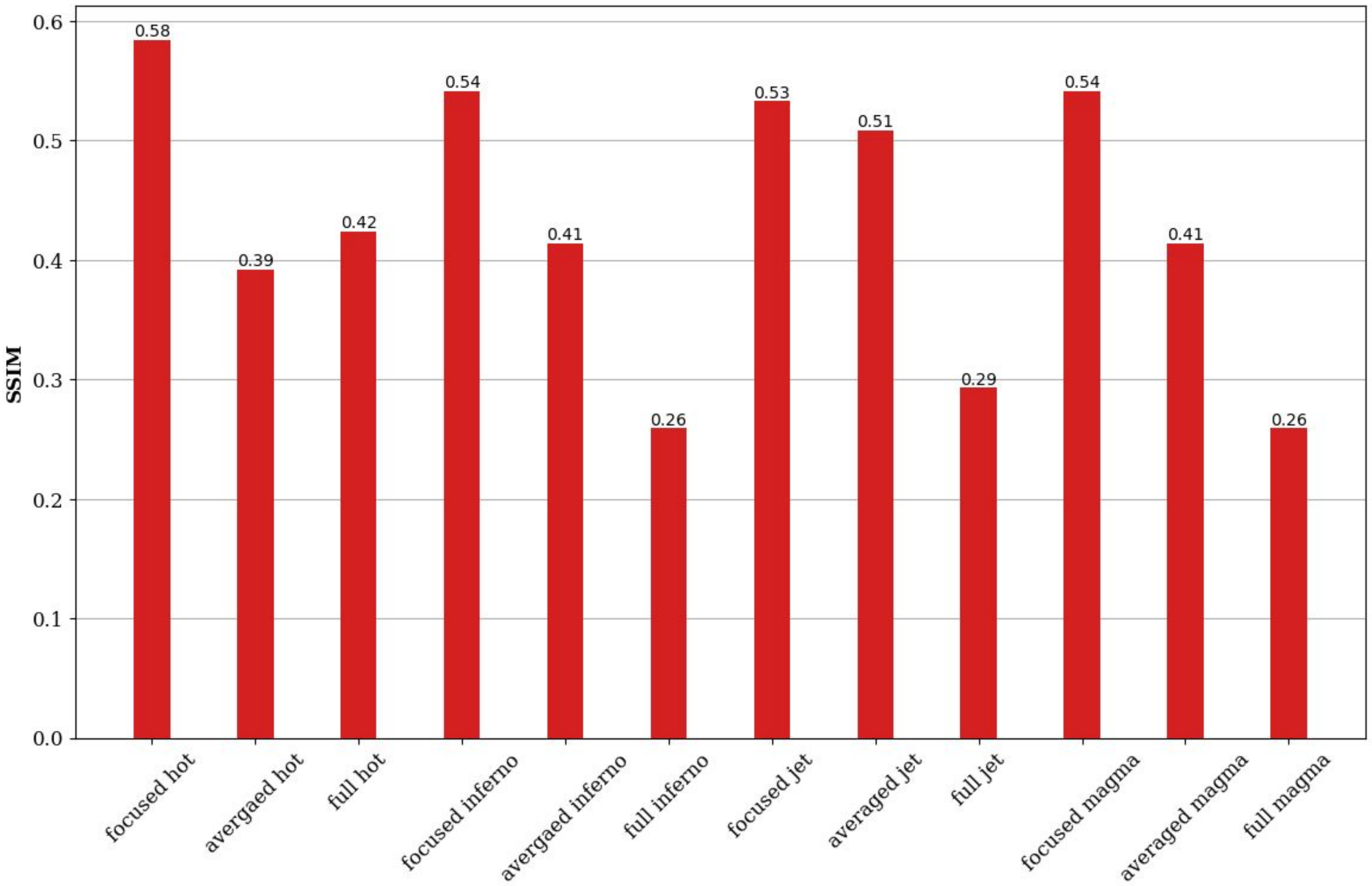


Clarity
0
10
20
30
40
50
41.78
8.20
6.66
50.06
6.41
3.08
51.06
12.17
4.62
50.06
6.41
3.08
focused hot
avergaed hot
full hot
focused inferno
avergaed inferno
full inferno
focused jet
averaged jet
full jet
focused magma
averaged magma
full magma

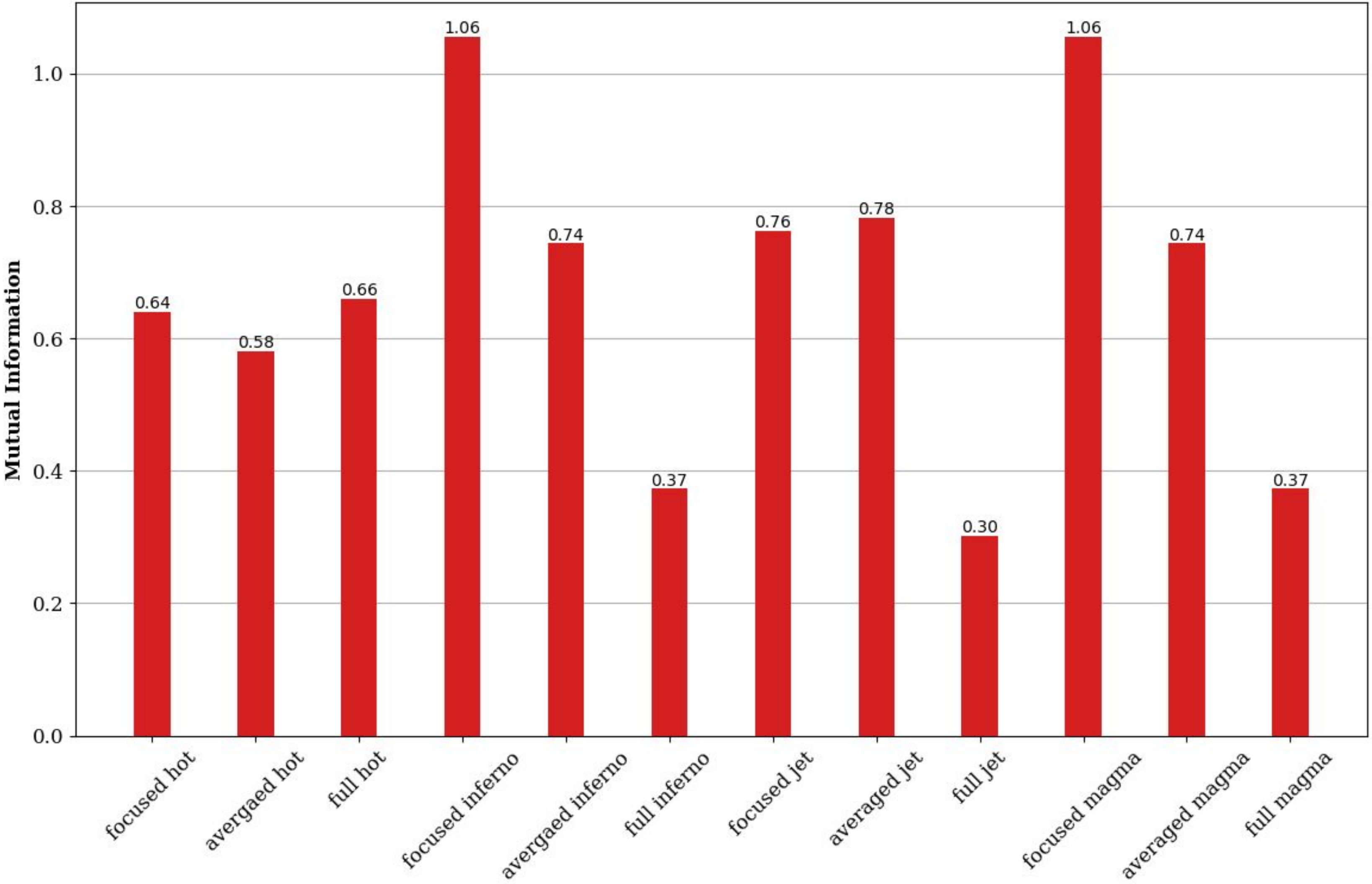


Entropy
6
5
4
3
2
1
0
5.58
3.65
3.53
5.95
3.42
1.87
5.35
4.48
2.44
5.95
3.42
1.87
focused hot
avergaed hot
full hot
focused inferno
avergaed inferno
full inferno
focused jet
averaged jet
full jet
focused magma
averaged magma
full magma

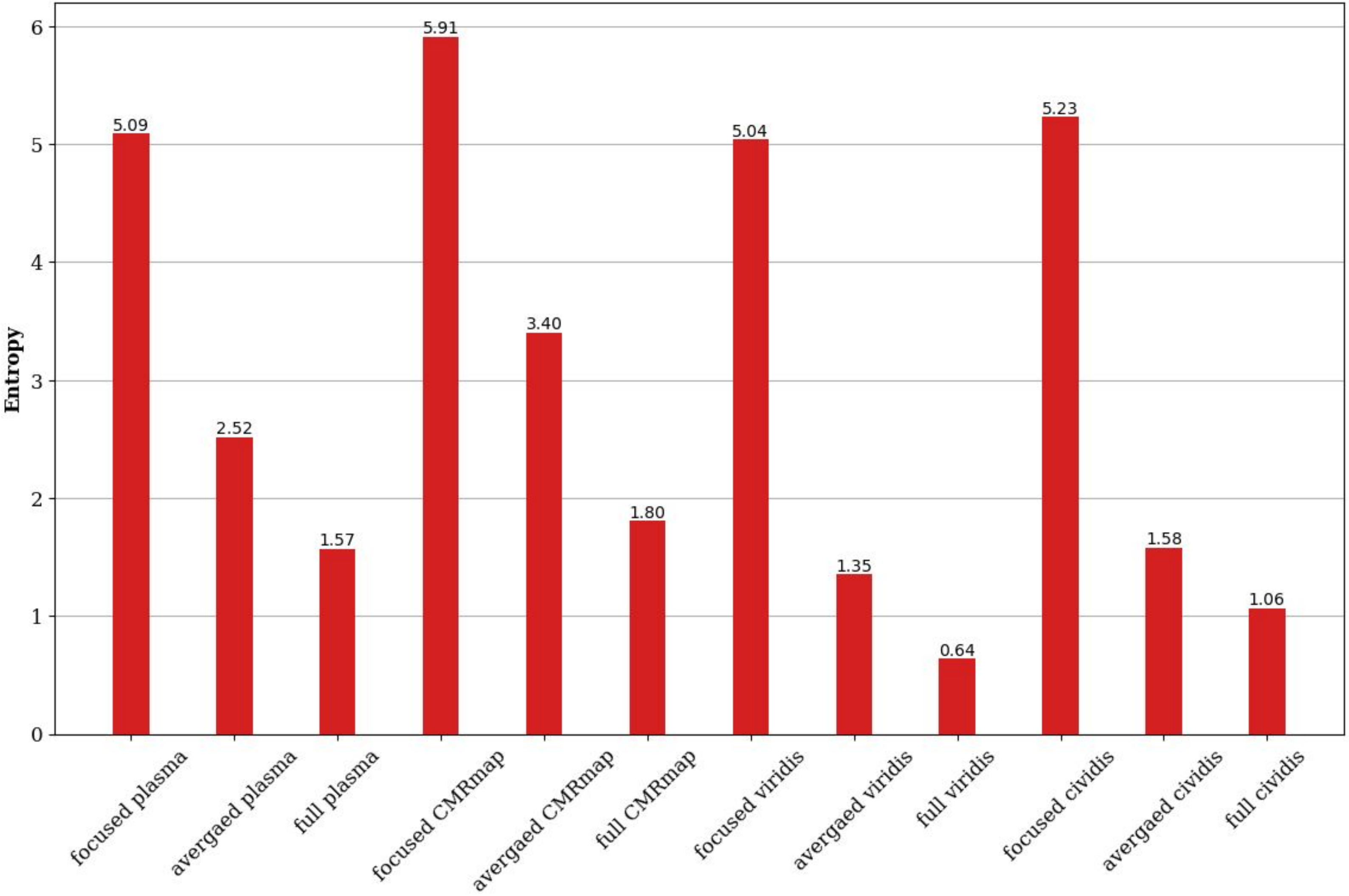

PSNR
0
10
20
30
40
44.03
23.89
23.88
46.79
23.50
9.90
43.59
32.34
12.87
46.79
23.50
9.90
focused hot
avergaed hot
full hot
focused inferno
avergaed inferno
full inferno
focused jet
averaged jet
full jet
focused magma
averaged magma
full magma



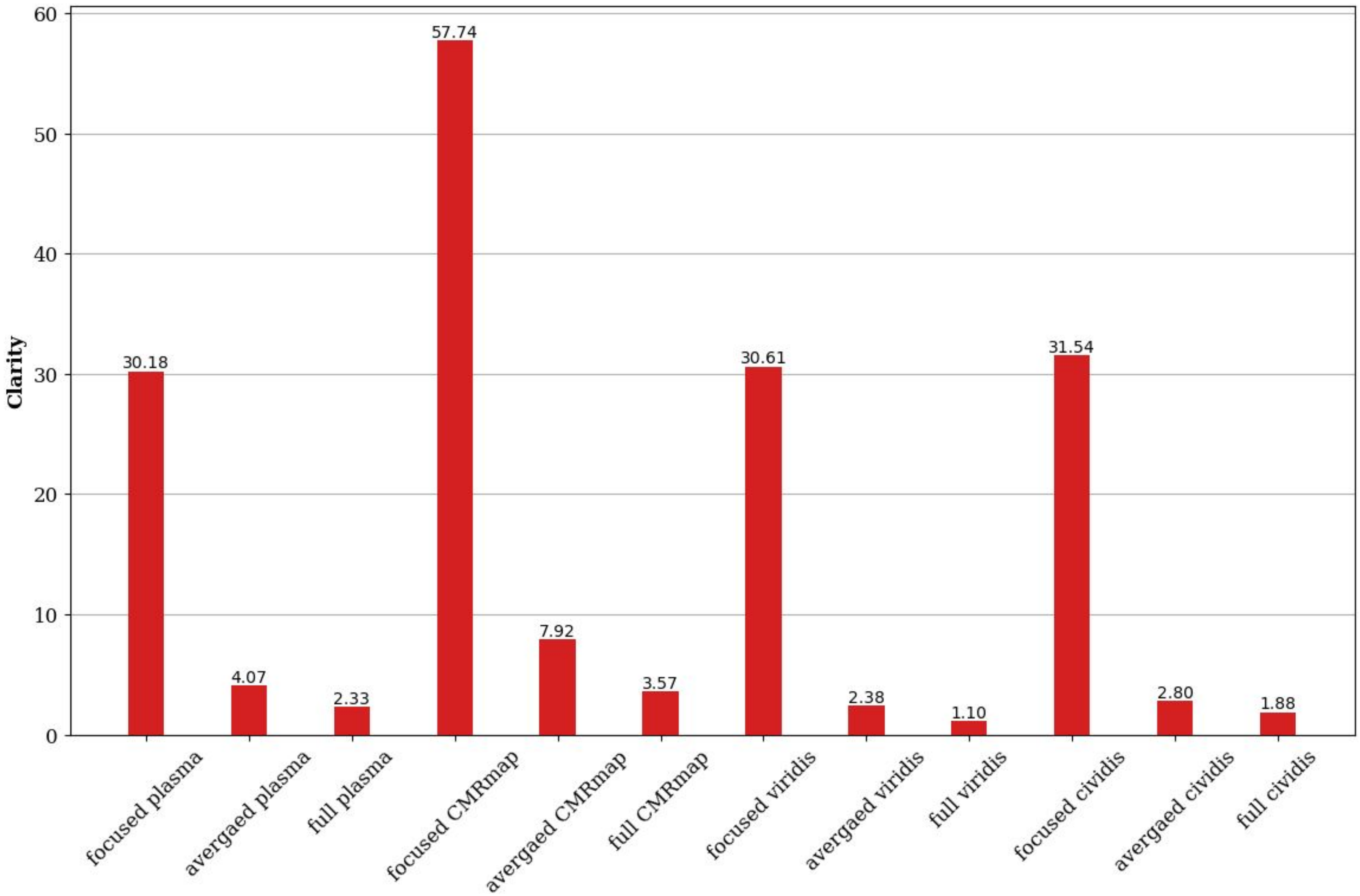
SSIM
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.58
0.39
0.42
0.54
0.41
0.26
0.53
0.51
0.29
0.54
0.41
0.26
focused hot
avergaed hot
full hot
focused inferno
avergaed inferno
full inferno
focused jet
averaged jet
full jet
focused magma
averaged magma
full magma

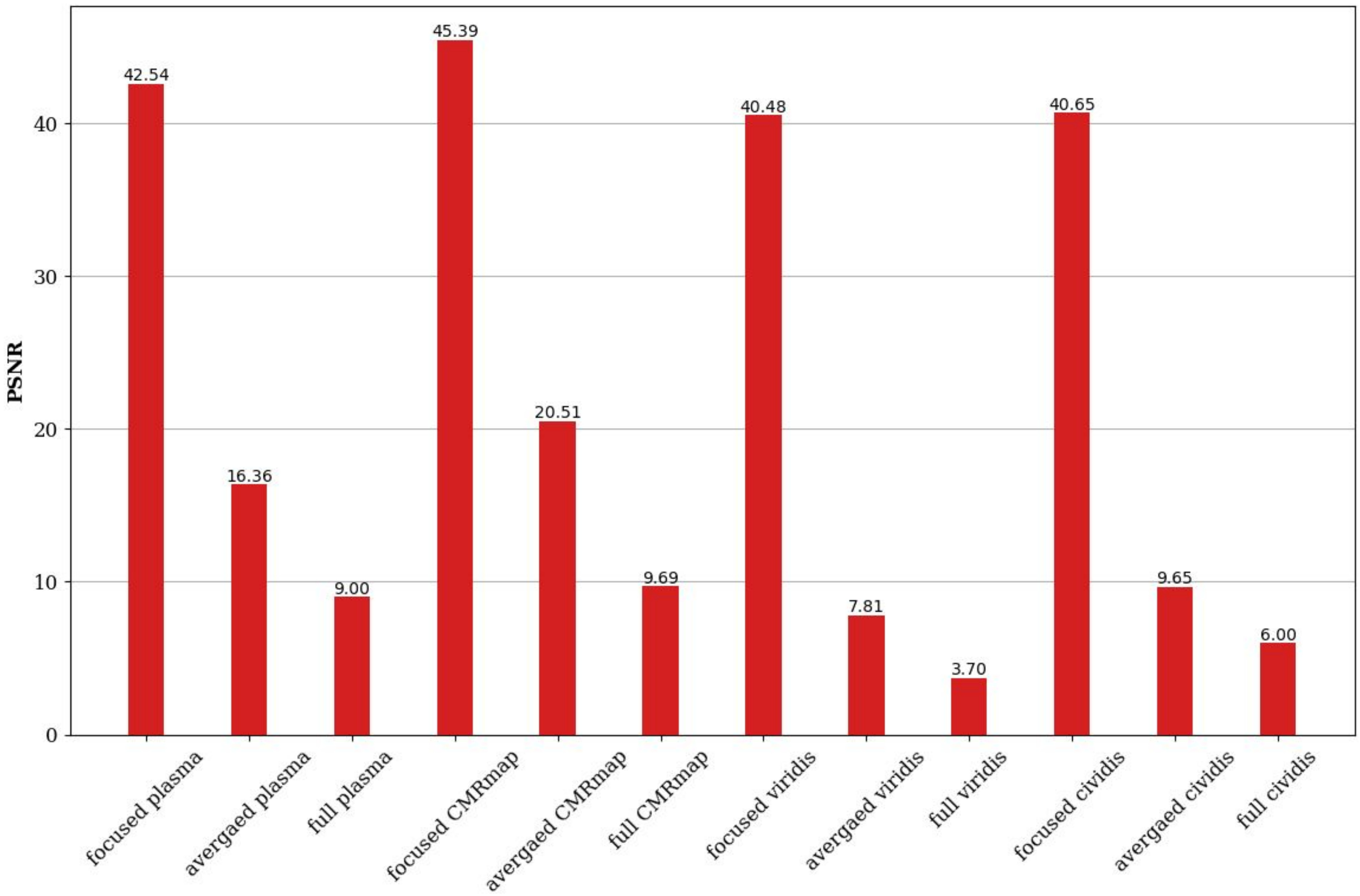


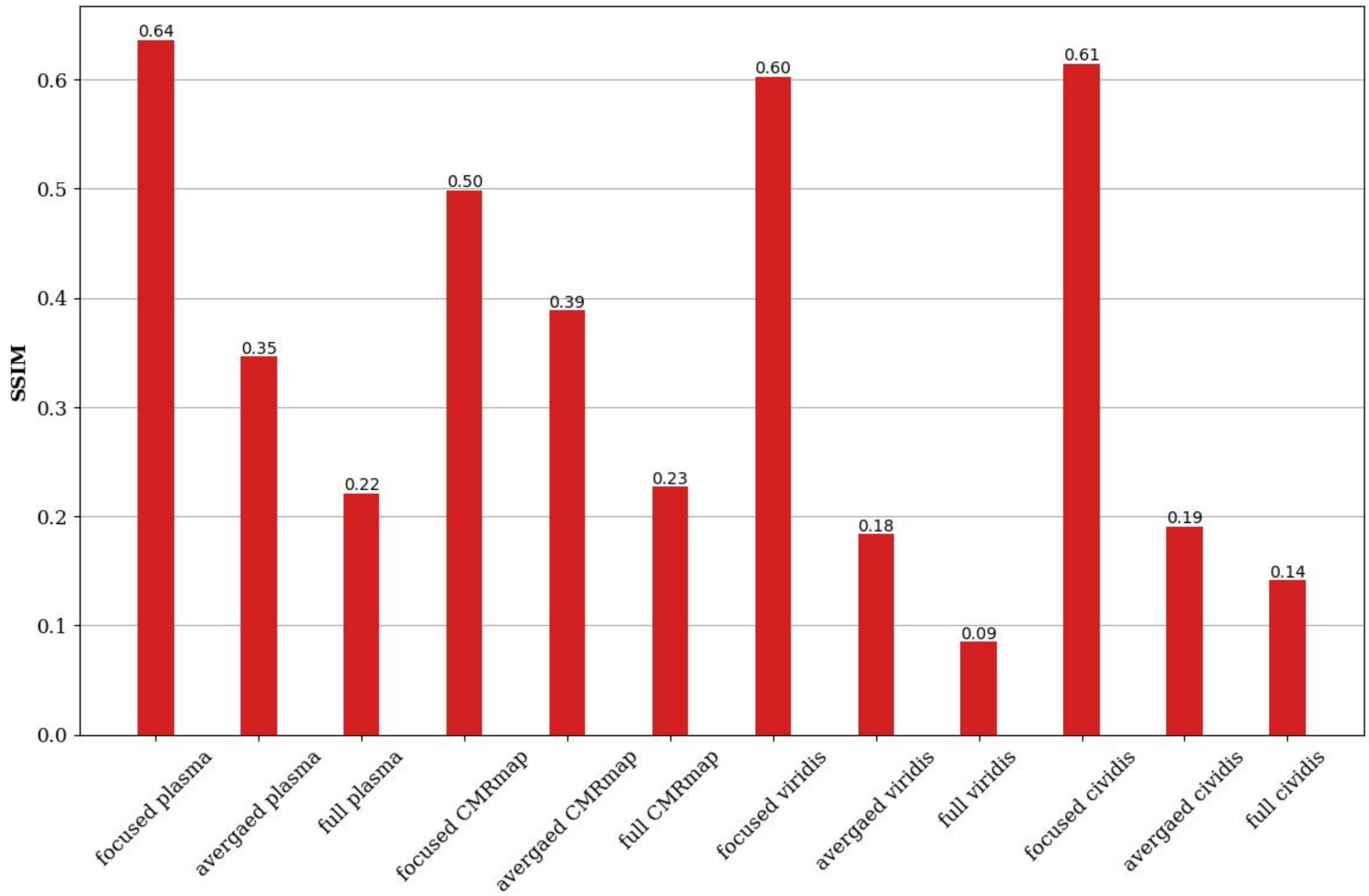
Mutual Information
0.0
0.2
0.4
0.6
0.8
1.0
0.64
0.58
0.66
1.06
0.74
0.37
0.76
0.78
0.30
1.06
0.74
0.37
focused hot
avergaed hot
full hot
focused inferno
avergaed inferno
full inferno
focused jet
averaged jet
full jet
focused magma
averaged magma
full magma



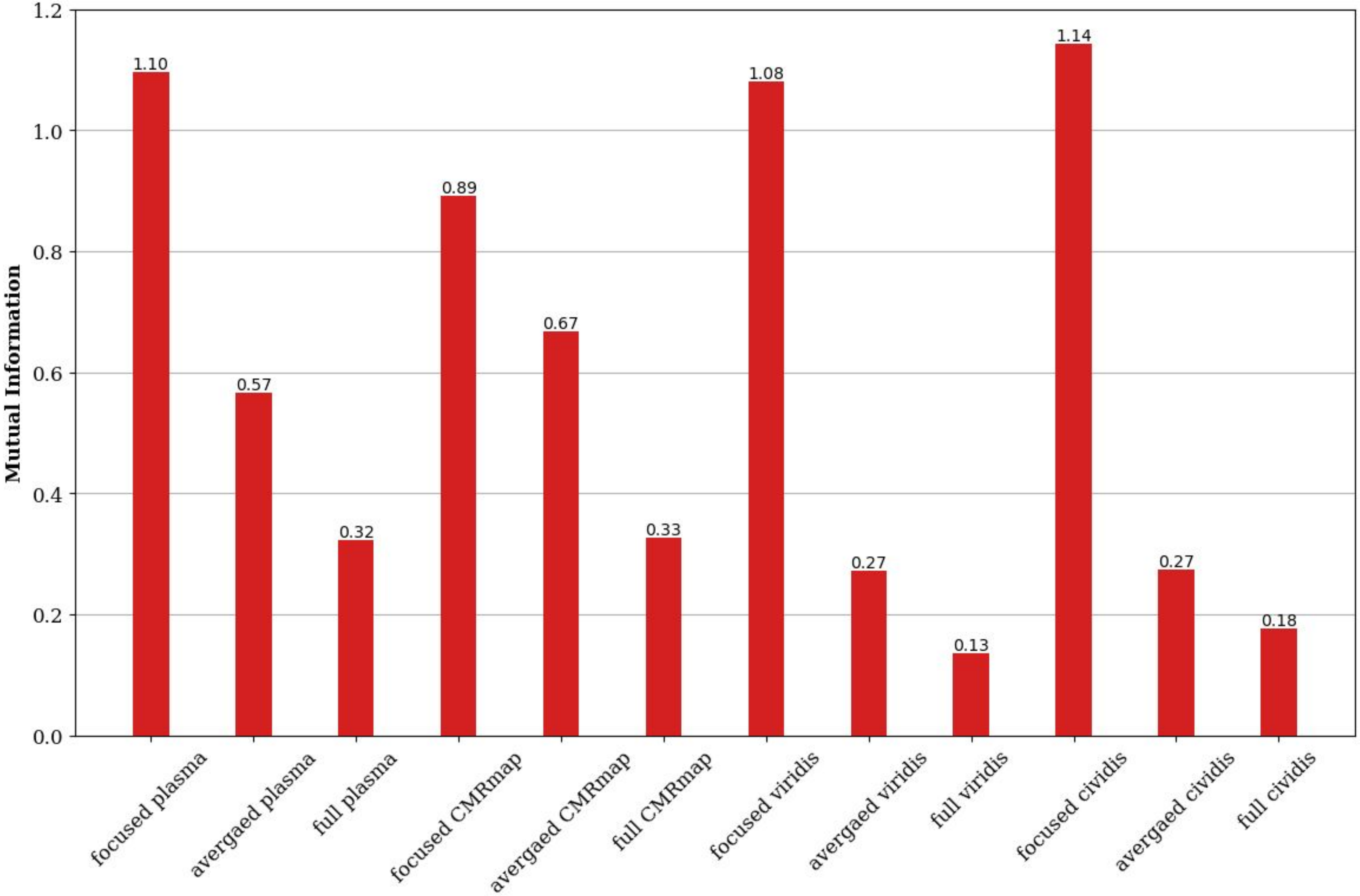
Entropy
0
1
2
3
4
5
6
5.09
2.52
1.57
5.91
3.40
1.80
5.04
1.35
0.64
5.23
1.58
1.06
focused plasma
avergaed plasma
full plasma
focused CMRmap
avergaed CMRmap
full CMRmap
focused viridis
avergaed viridis
full viridis
focused cividis
avergaed cividis
full cividis


Clarity
0
10
20
30
40
50
60
30.18
4.07
2.33
57.74
7.92
3.57
30.61
2.38
1.10
31.54
2.80
1.88
focused plasma
avergaed plasma
full plasma
focused CMRmap
avergaed CMRmap
full CMRmap
focused viridis
avergaed viridis
full viridis
focused cividis
avergaed cividis
full cividis

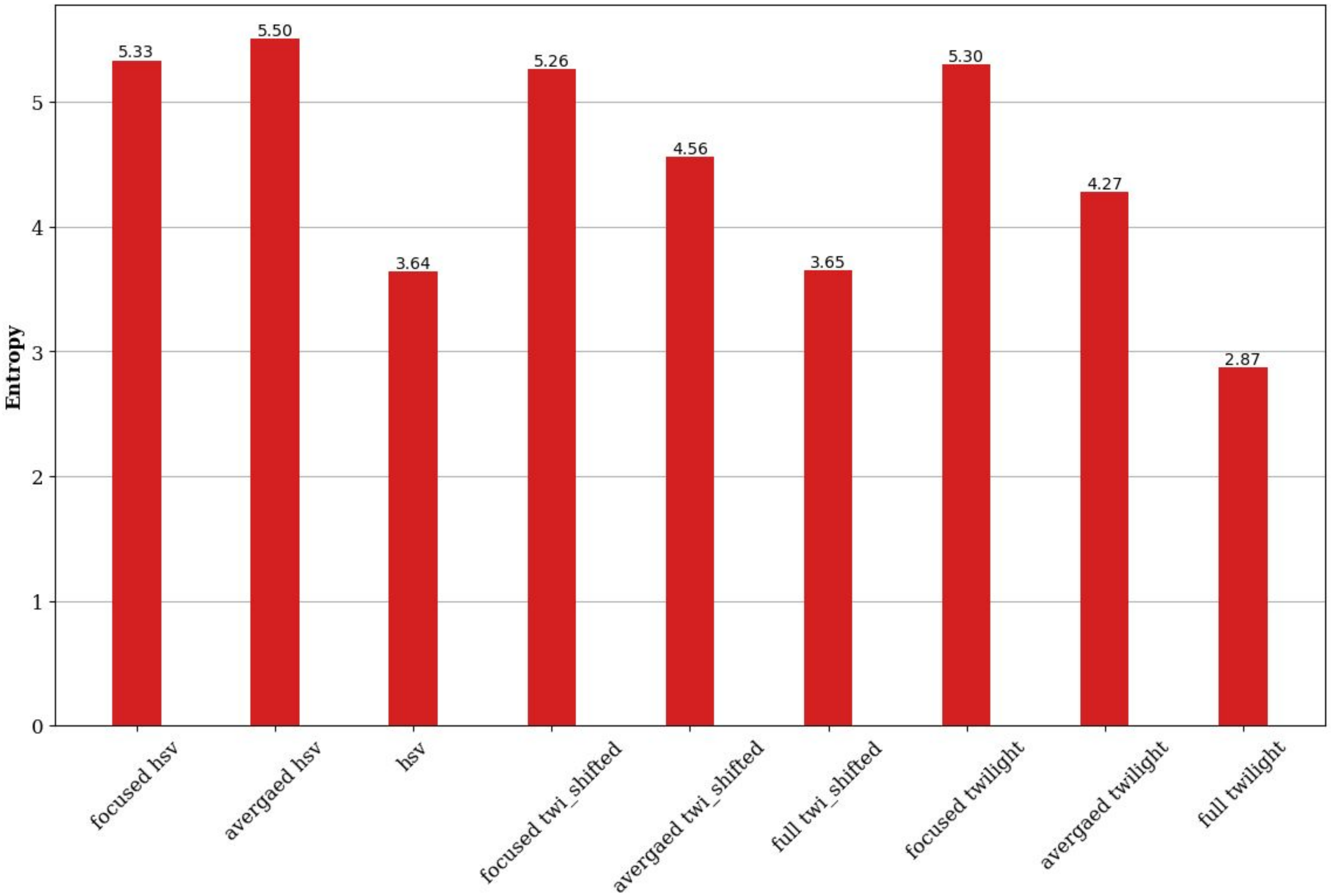

PSNR
0
10
20
30
40
42.54
16.36
9.00
45.39
20.51
9.69
40.48
7.81
3.70
40.65
9.65
6.00
focused plasma
avergaed plasma
full plasma
focused CMRmap
avergaed CMRmap
full CMRmap
focused viridis
avergaed viridis
full viridis
focused cividis
avergaed cividis
full cividis



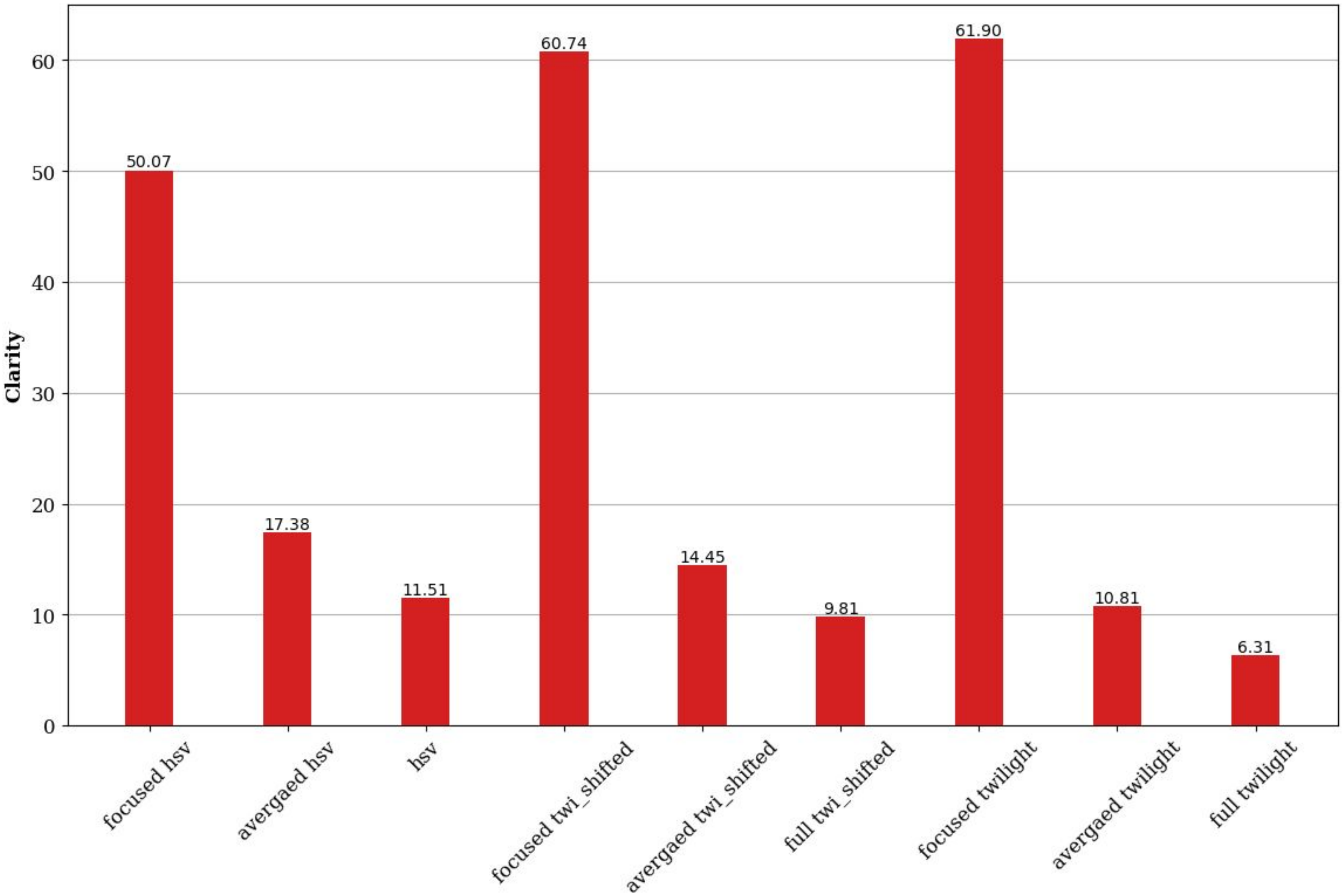
SSIM
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.64
0.35
0.22
0.50
0.39
0.23
0.60
0.18
0.09
0.61
0.19
0.14
focused plasma
avergaed plasma
full plasma
focused CMRmap
avergaed CMRmap
full CMRmap
focused viridis
avergaed viridis
full viridis
focused cividis
avergaed cividis
full cividis

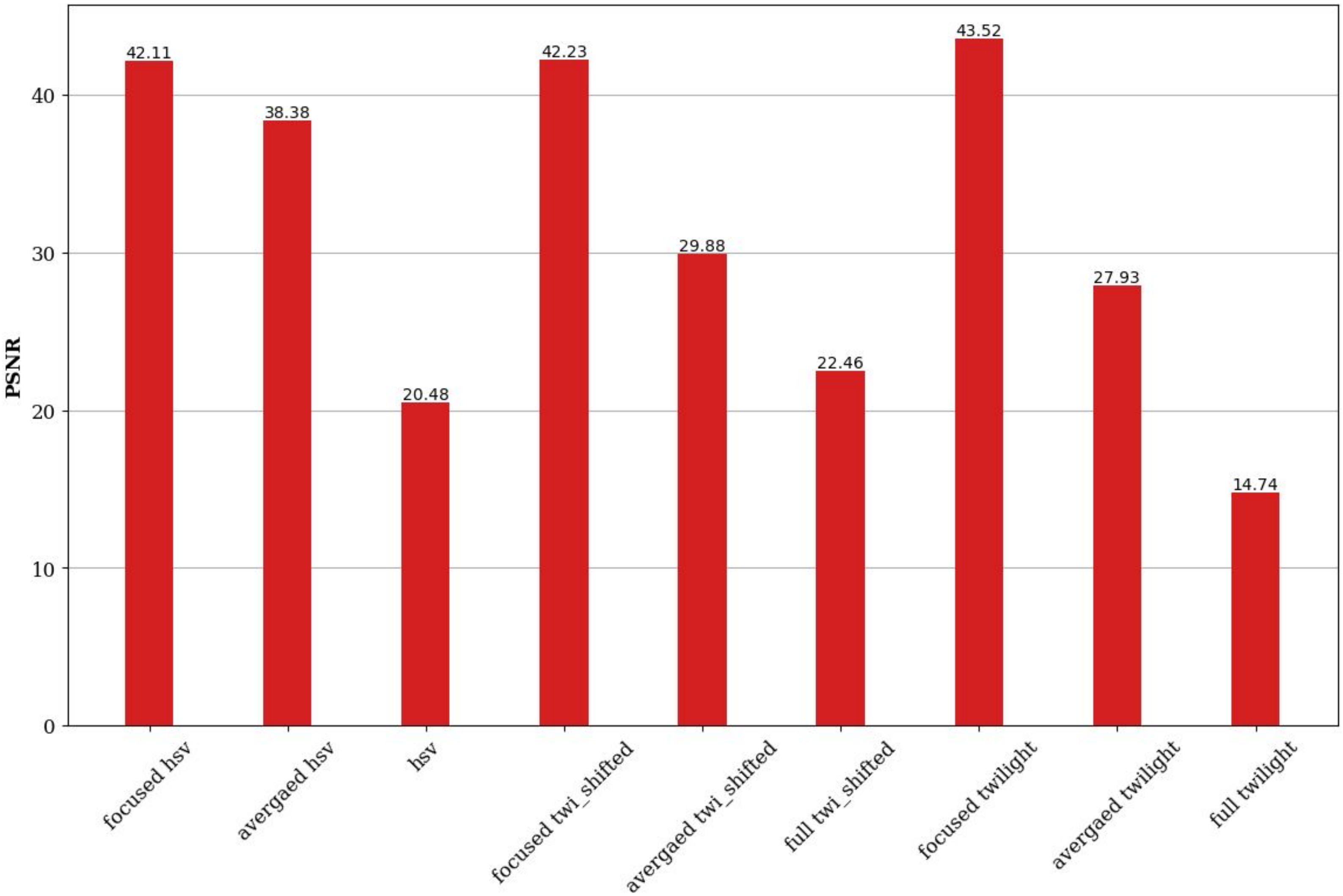


Mutual Information
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1.10
0.57
0.32
0.89
0.67
0.33
1.08
0.27
0.13
1.14
0.27
0.18
focused plasma
avergaed plasma
full plasma
focused CMRmap
avergaed CMRmap
full CMRmap
focused viridis
avergaed viridis
full viridis
focused cividis
avergaed cividis
full cividis

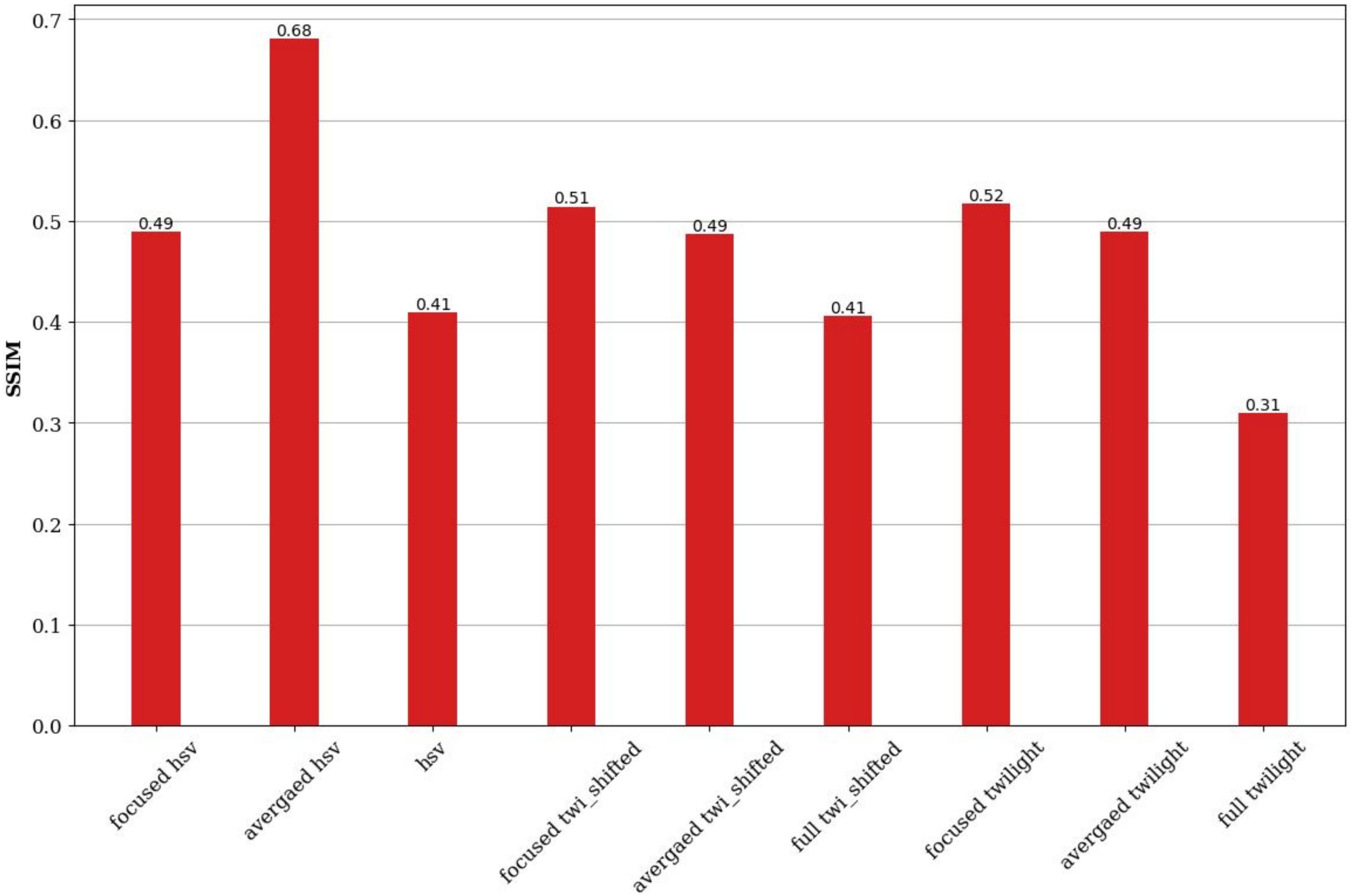


Entropy
0
1
2
3
4
5
5.33
5.50
3.64
5.26
4.56
3.65
5.30
4.27
2.87
focused hsv
avergaed hsv
hsv
focused twi_shifted
avergaed twi_shifted
full twi_shifted
focused twilight
avergaed twilight
full twilight

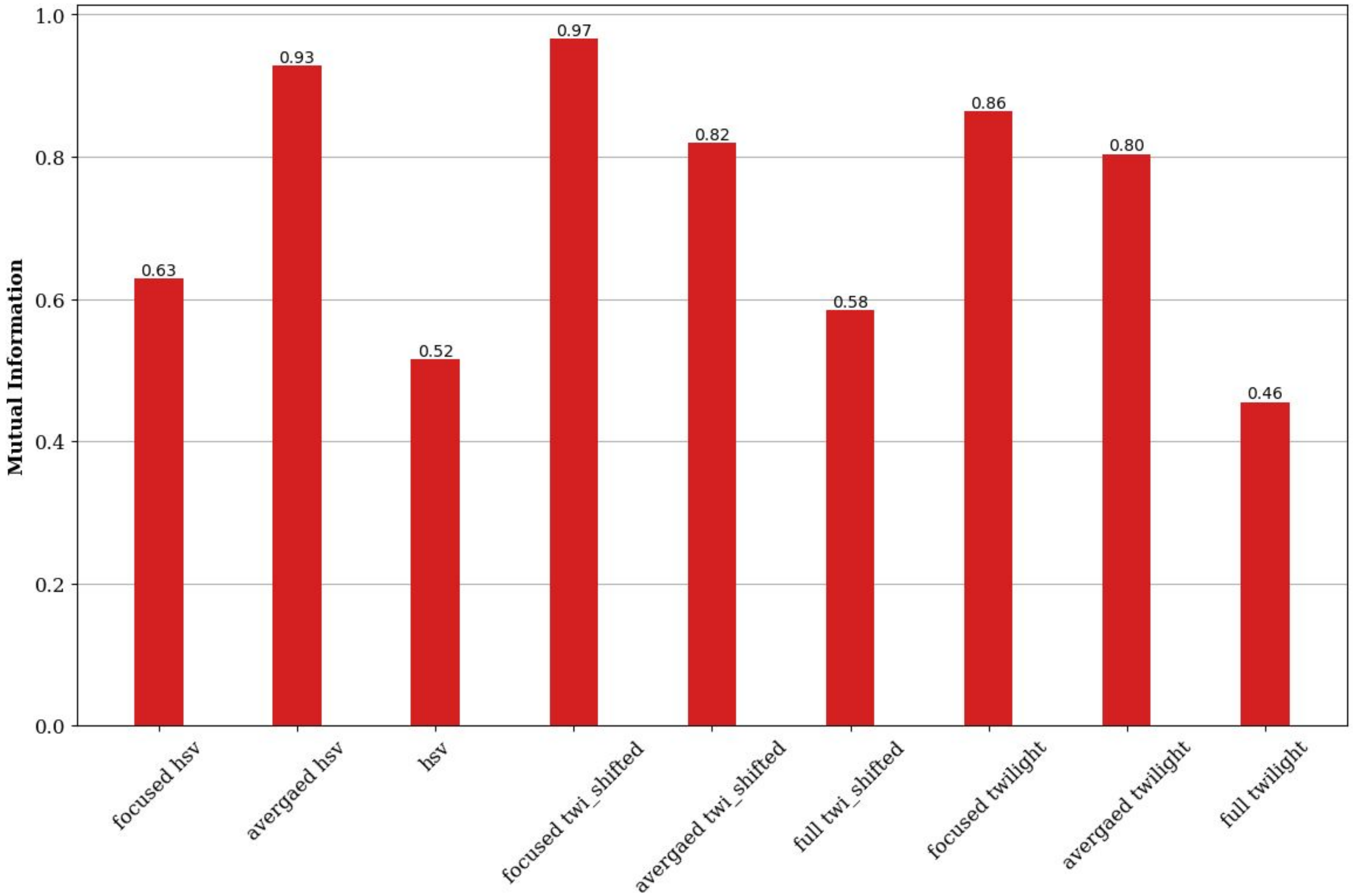

Clarity
0
10
20
30
40
50
60
50.07
17.38
11.51
60.74
14.45
9.81
61.90
10.81
6.31
focused hsv
avergaed hsv
hsv
focused twi_shifted
avergaed twi_shifted
full twi_shifted
focused twilight
avergaed twilight
full twilight



PSNR
0
10
20
30
40
42.11
38.38
20.48
42.23
29.88
22.46
43.52
27.93
14.74
focused hsv
avergaed hsv
hsv
focused twi_shifted
avergaed twi_shifted
full twi_shifted
focused twilight
avergaed twilight
full twilight



0.68
0.49
0.41
0.51
0.49
0.41
0.52
0.49
0.31
SSIM
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
focused hsv
avergaed hsv
hsv
focused twi_shifted
avergaed twi_shifted
full twi_shifted
focused twilight
avergaed twilight
full twilight



Mutual Information
1.0
0.8
0.6
0.4
0.2
0.0
0.63
0.93
0.52
0.97
0.82
0.58
0.86
0.80
0.46
focused hsv
avergaed hsv
hsv
focused twi_shifted
avergaed twi_shifted
full twi_shifted
focused twilight
avergaed twilight
full twilight

Failure Rates

Color Map	Fails	Fails %	Color Map	Fails	Fails %	Color Map	Fails	Fails %	Color Map	Fails	Fails %
Hot focused	0	0.00	Magma focused	1	0.02	Cividis focused	3	0.05	Twilight focused	0	0.00
Hot averaged	32	0.57	Magma averaged	29	0.52	Cividis averaged	42	0.75	Twilight averaged	19	0.34
Hot full	33	0.59	Magma full	44	0.79	Cividis full	48	0.86	Twilight full	37	0.66
Inferno focused	1	0.02	Plasma focused	3	0.05	HSV focused	0	0.00	CMRmap focused	2	0.04
Inferno averaged	29	0.52	Plasma averaged	38	0.68	HSV averaged	9	0.16	CMRmap averaged	32	0.57
Inferno full	24	0.43	Plasma full	45	0.80	HSV full	30	0.54	CMRmap full	44	0.79
Jet focused	0	0.00	Viridis focused	8	0.14	Twi-Shifted focused	0	0.00			0.00
Jet averaged	20	0.36	Viridis averaged	44	0.79	Twi-Shifted averaged	18	0.32			0.00
Jet full	38	0.68	Viridis full	51	0.91	Twi-Shifted full	33	0.59			0.00

To Results per Metric (focused range)

	Entropy		Clarity		PSNR		SSIM		MI	
1	Inferno	5.95	Twilight	61.90	Inferno	46.79	Plasma	0.64	Cividis	1.14
2	Magma	5.95	Twilight Shifted	60.74	Magma	46.79	Cividis	0.61	Plasma	1.10
3	CMRmap	5.91	CMRmap	57.74	CMRmap	45.39	Viridis	0.60	Viridis	1.08
4	Hot	5.58	Jet	51.06	Hot	44.03	Hot	0.58	Inferno	1.06
5	Jet	5.35	Inferno & Magma	50.06	Jet	43.59	Inferno & Magma	0.54	Magma	1.06

To-Do Next

- ~~One bar chart per metric~~
    - Three groups of bars (all colormaps, best colormap), one per range, plot with SD
    - Total: 6 bars per chart
    - Idea: compare all ranges, show best colormap per range and metric
    - Show that focused range is the best
    - What colormaps are more frequent the best
    - Difference between best and the average colormap (standard deviation) : per metric
- ~~Example ground truth, stitched result, comparison of the ranges~~

Meeting
25/06/2024

Agenda

- New evaluation pipeline
- Range Selection Methods Tested
- Preliminary Evaluation Results

New Pipeline

- Combines a stitching pipeline and an evaluation pipeline into a big wrapper function.
- Runs all possible dataset pairs, evaluates the results, then aggregates them.
- Copy of the notebook can be found here.

Range Selection Methods Tested

1. Automatic

    Selects the most frequent pixel values of each image in the dataset. The min and max of these frequent pixels are then selected as the cmap range.

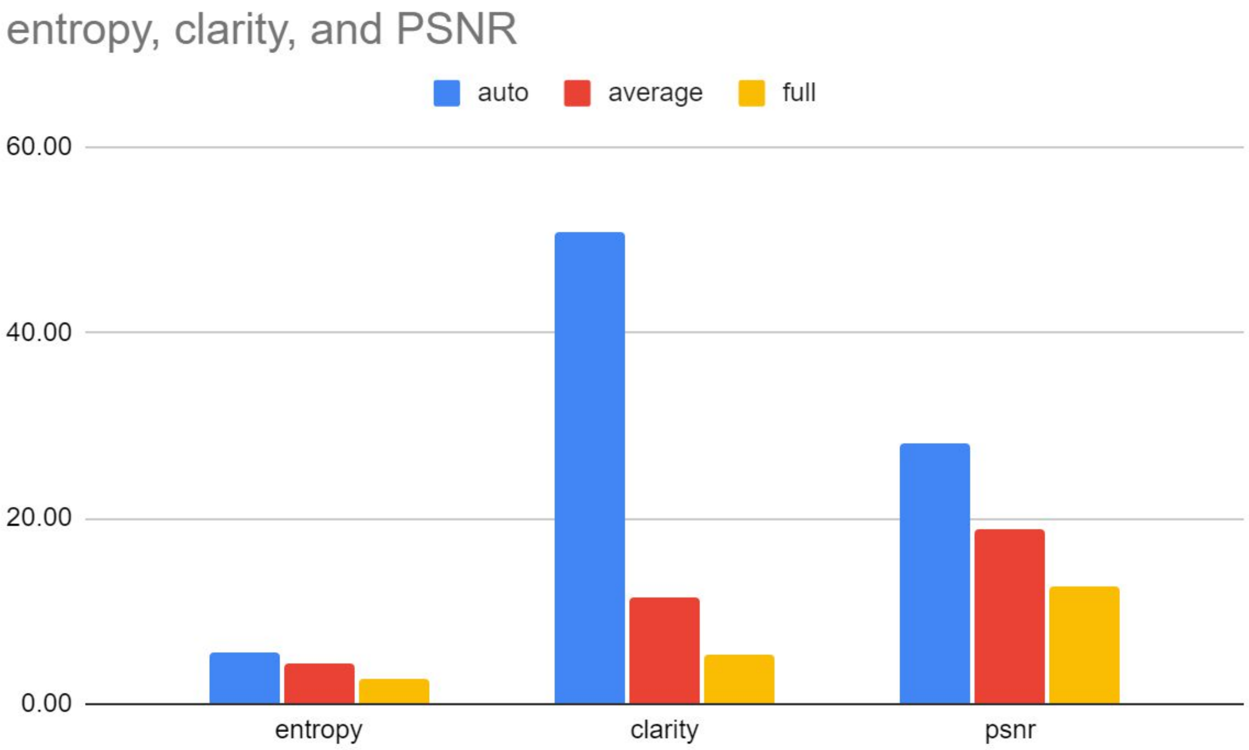
2. Averaged

    Gets the max and min values of each image in the dataset. Sets the average min and average max to the cmap range.

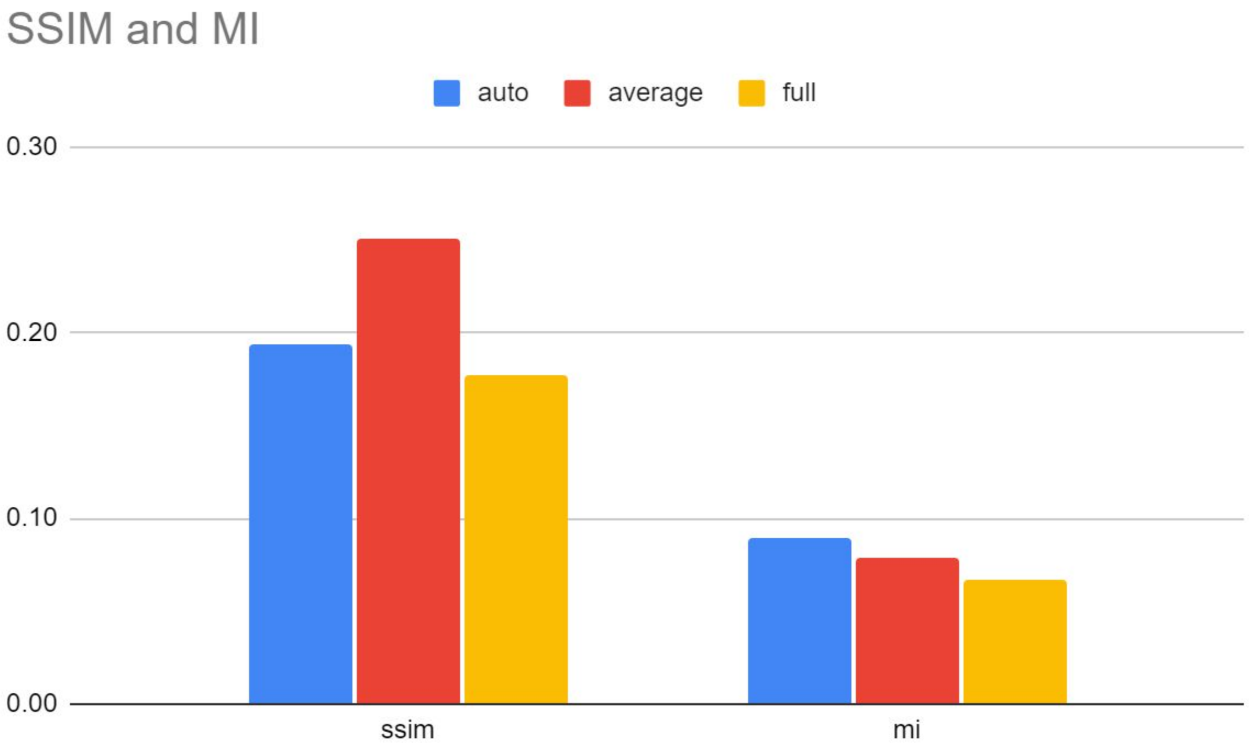
3. Full

    Selects the highest max and lowest min values in the dataset as the cmap range.

Preliminary Evaluation Results



Preliminary Evaluation Results



To-Do Next

- ~~Manually remove outliers~~
- ~~Different Cmaps (one stands out)~~
- ~~Check MI (rgb effects)~~
- SD of the metrics then plot that
- ~~Percentage of failures~~
- Compare with commercial softwares

- ~~Stitch thermals using RGB features then use as GT~~
- Mini paper — IEEE format (poster done later)

Meeting
20/06/2024

Agenda

- General Observations
- Stitching Pipeline
  - Different Cmaps
  - Visible Patterns
    - Bus bars
    - Shadows
  - Optimal Map Range Selection
- Evaluation

General Observations

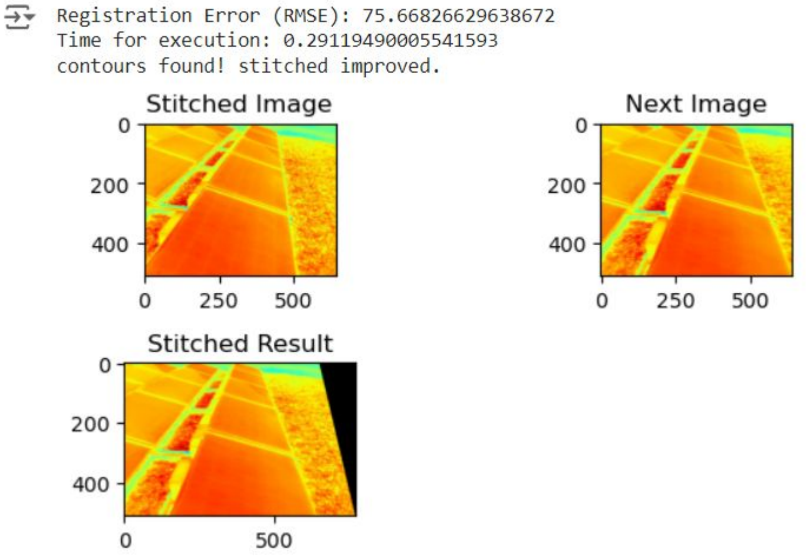
- Close-up images of solar panels have little to no differentiation, and therefore feature-based stitching is near impossible.
- Wider angle shots and shots with outside reference objects have better promise.
- Geographical information may be more helpful, though it would need to be extremely accurate for consecutive low-altitude shots.
- Out of curiosity, how would solar panel defects look in thermal images?

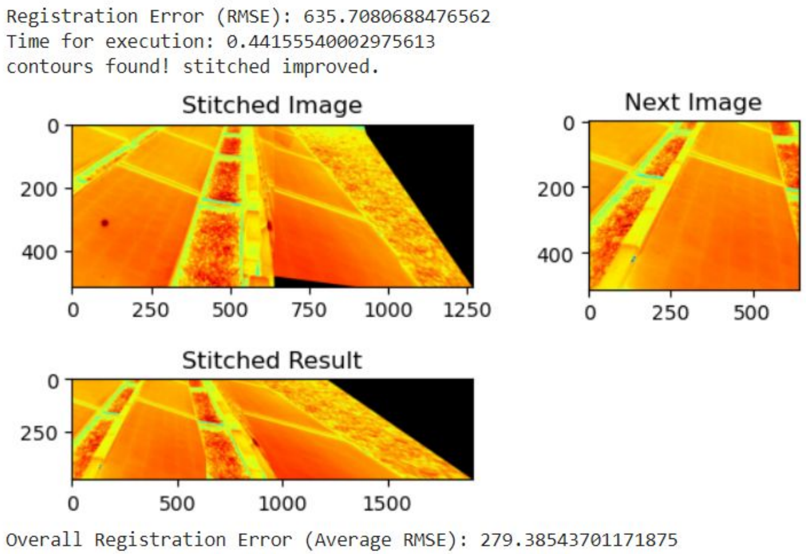
Stitching Pipeline

Stitching Pipeline

Pipeline was adapted from the 2020 GitHub project found here.

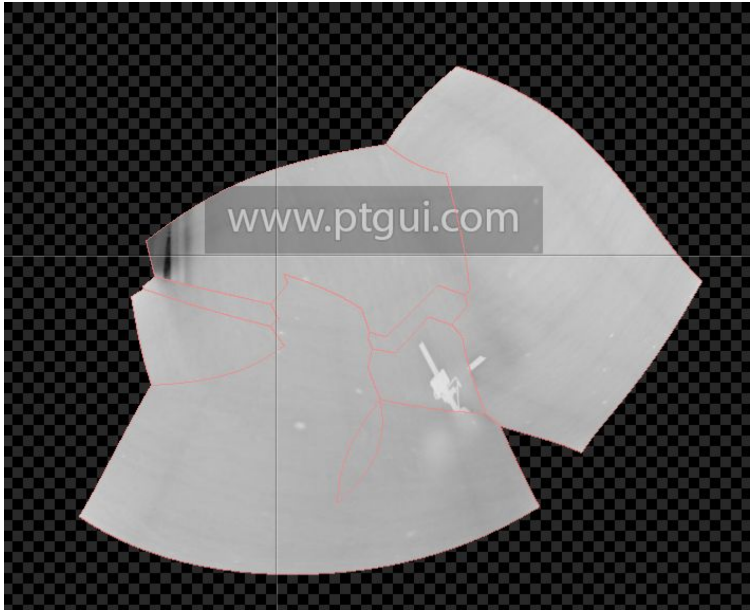
Copy of the edited pipeline can be found here.



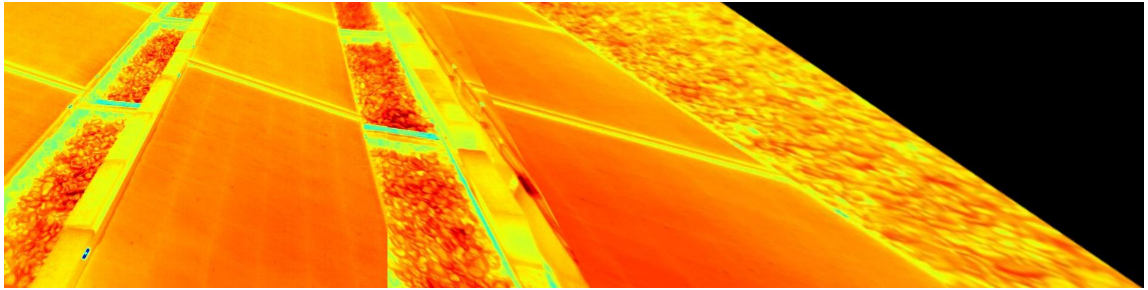


Different Cmaps

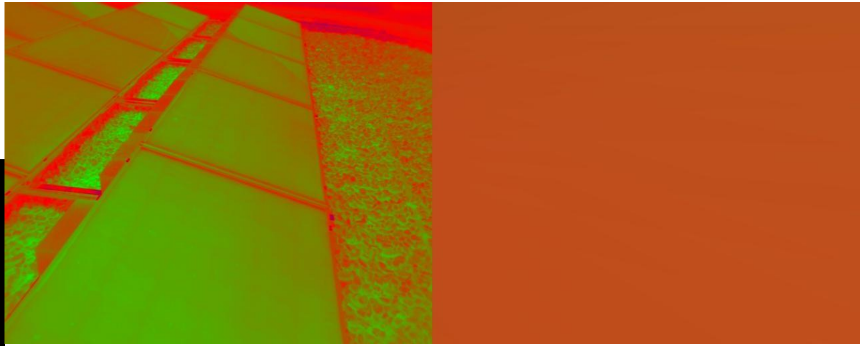
- Theoretically, more variable/higher contrast color maps perform better when it comes to feature detection.

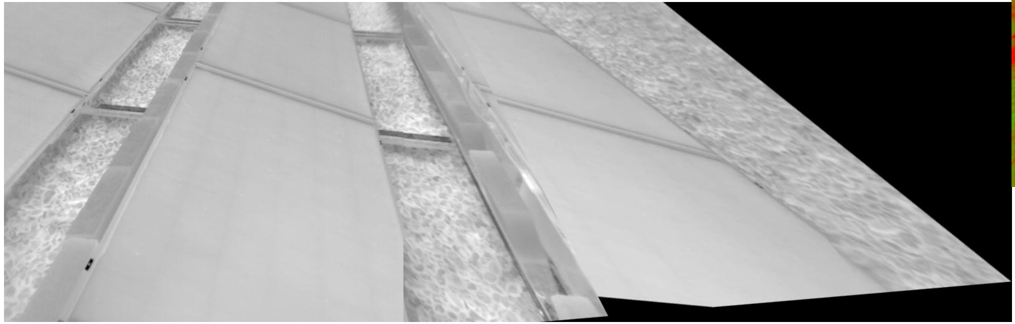


Different Cmaps



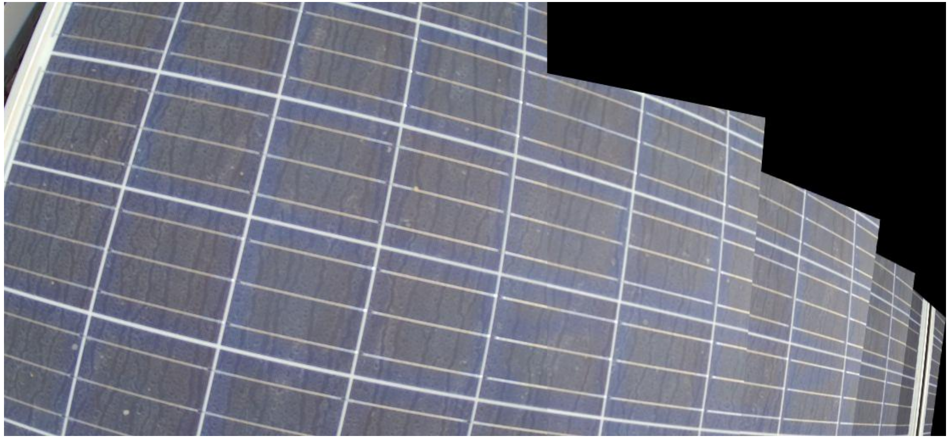
Dataset 8

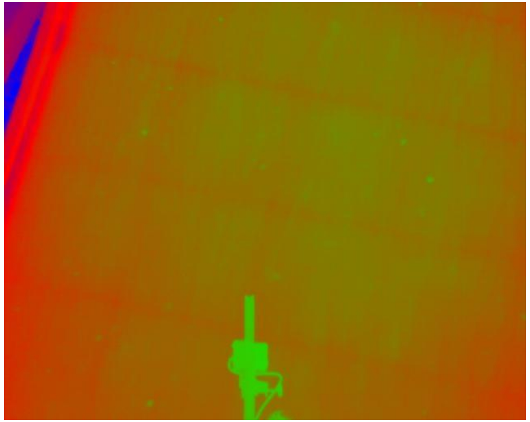


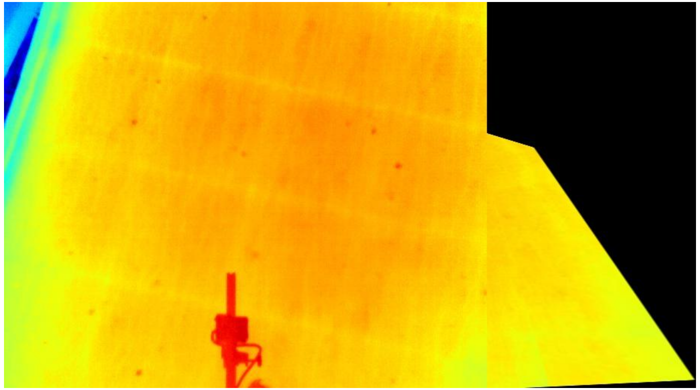


Different Cmaps

Dataset 16



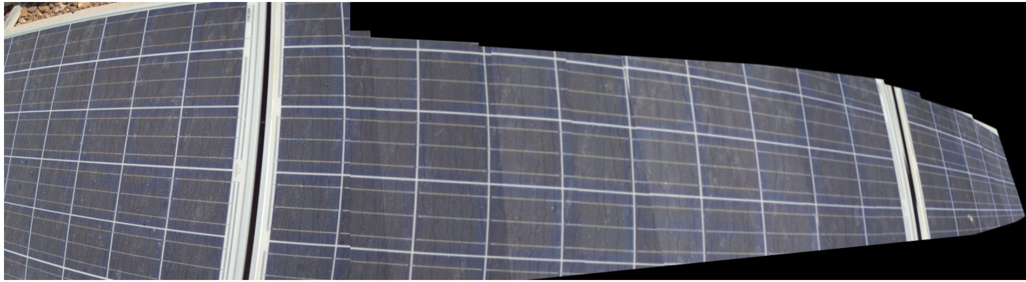




Visible Patterns: Bus Bars

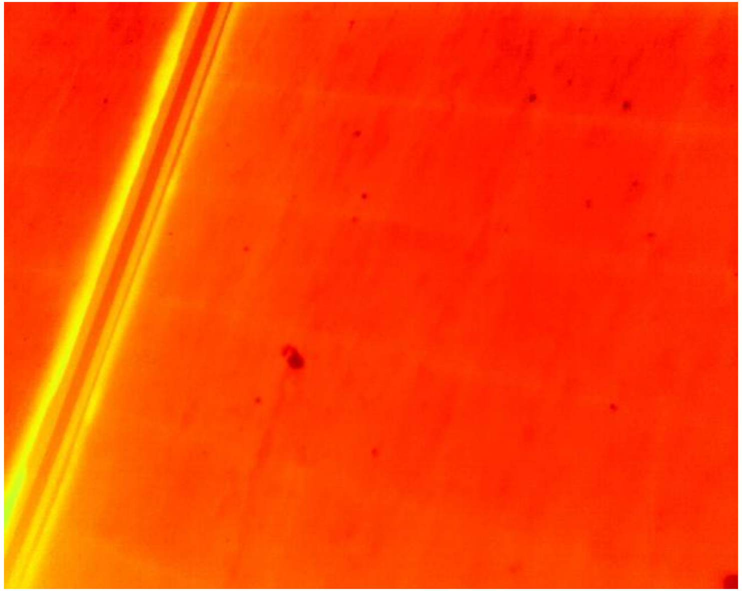
- Not at all visible, unfortunately.

Dataset 4



Visible Patterns: Bus Bars

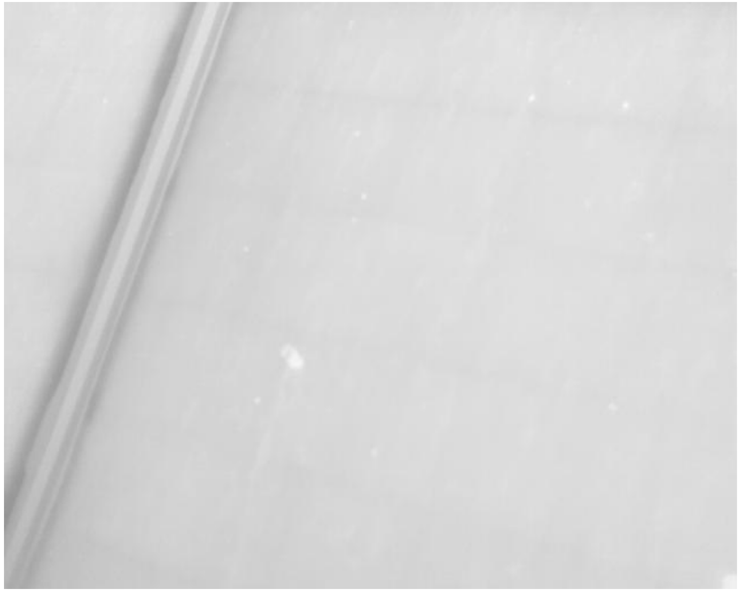
- Not at all visible, unfortunately.



Dataset 4 - Cmap jet

Visible Patterns: Bus Bars

- Not at all visible, unfortunately.



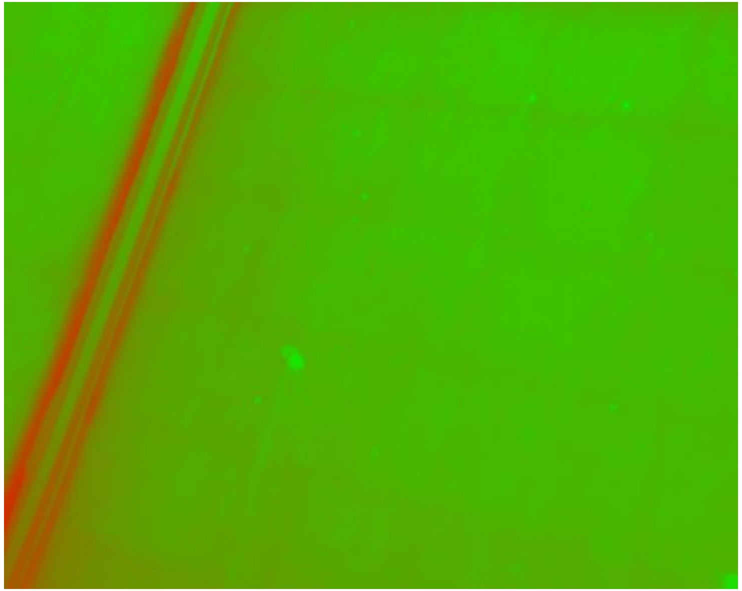
Dataset 4

Cmap gray

```
No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.
```

Visible Patterns: Bus Bars

- Not at all visible, unfortunately.



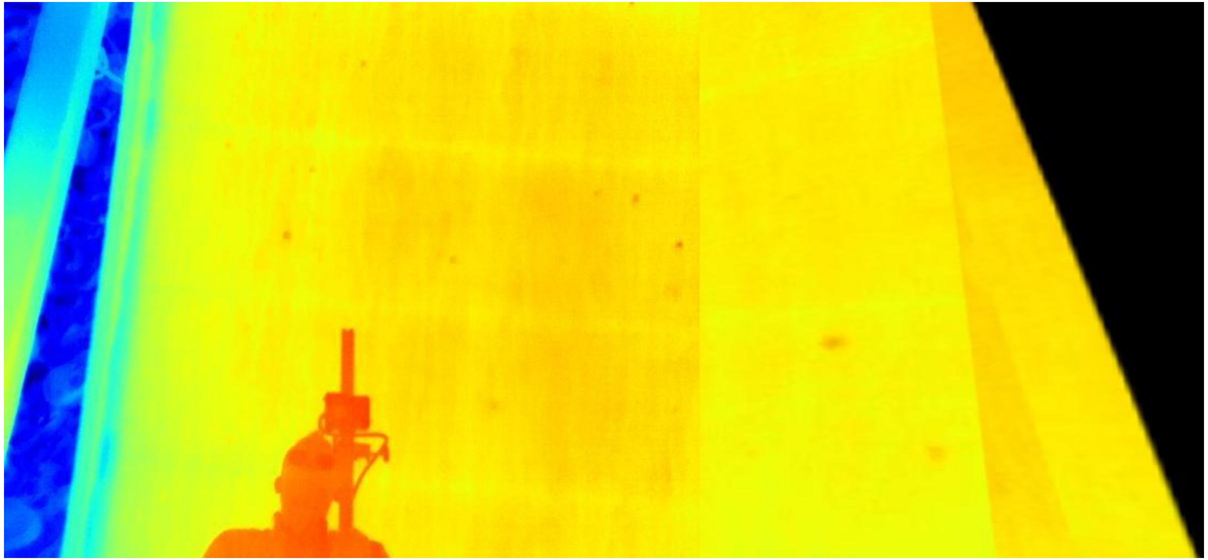
Dataset 4

Cmap brg

```
No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.

No keypoints detected this iteration; skipped.
```

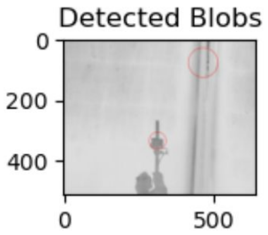
Visible Patterns: Shadows

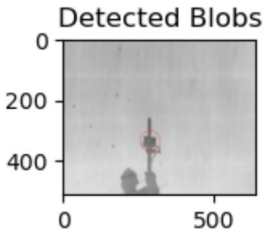
Dataset 3 (first 4 images) stitched without blob detection.

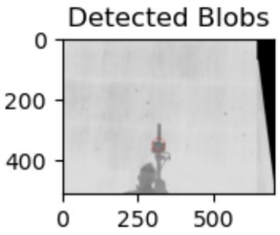


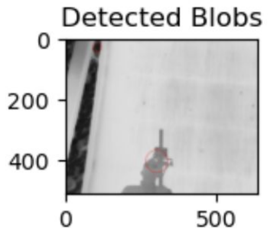
Visible Patterns: Shadows

Dataset 3 with blob detection & exclusion; needs a lot more work.









Visible Patterns: Shadows

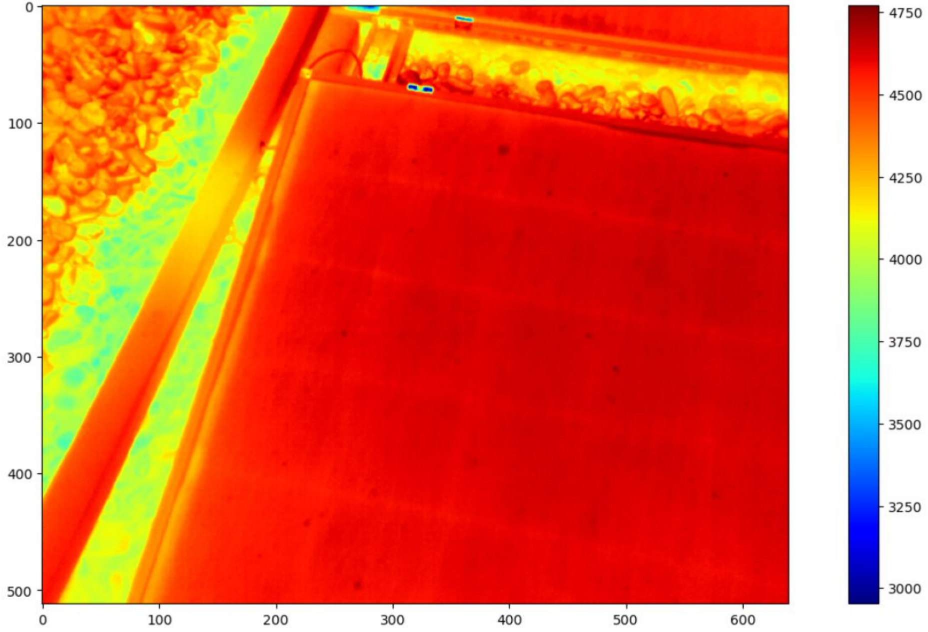
```python
def detect_blobs(image):
    # Setup SimpleBlobDetector parameters.
    params = cv2.SimpleBlobDetector_Params()

    # Change thresholds
    params.minThreshold = 30

    params.filterByArea = True
    params.minArea = 200

    params.filterByCircularity = False

    params.filterByConvexity = False
    # params.minConvexity = 0.5

    params.filterByInertia = False
    # params.minInertiaRatio = 0.2

    detector = cv2.SimpleBlobDetector_create(params)
    keypoints = detector.detect(image)

    # Draw detected blobs
    im_with_keypoints = cv2.drawKeypoints(image, keypoints, np.array([]), (0, 0, 255), cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

    return keypoints, im_with_keypoints
```

Current parameters.

Optimal Map Range Selection

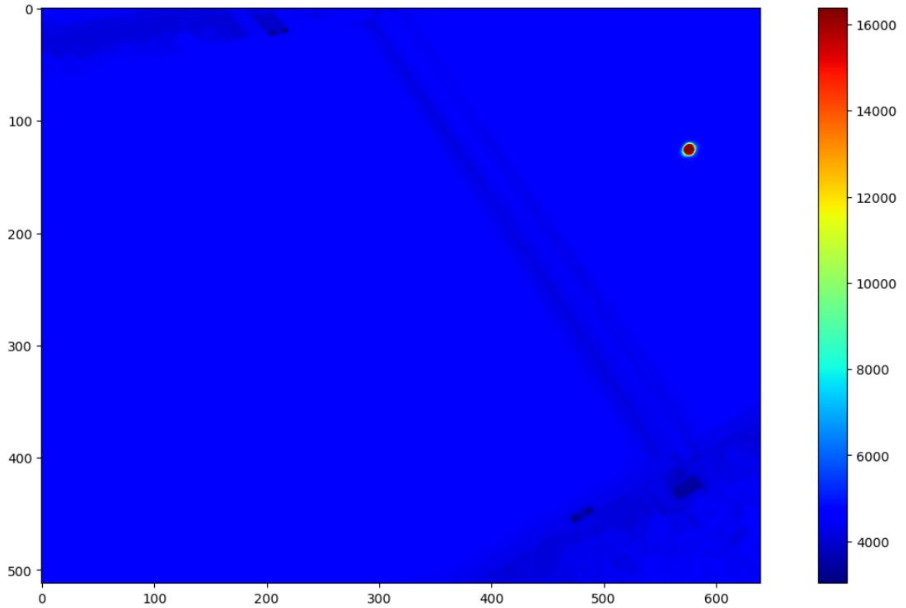
- Oftentimes a few images in the dataset will contain a small region of extremely high thermal value. Including that small region in the unified colormap of the dataset comes at the cost of losing much of the details in the rest of the database.
- Recurring example of this is sun flare areas.

Optimal Map Range Selection



Dataset 1, img 1

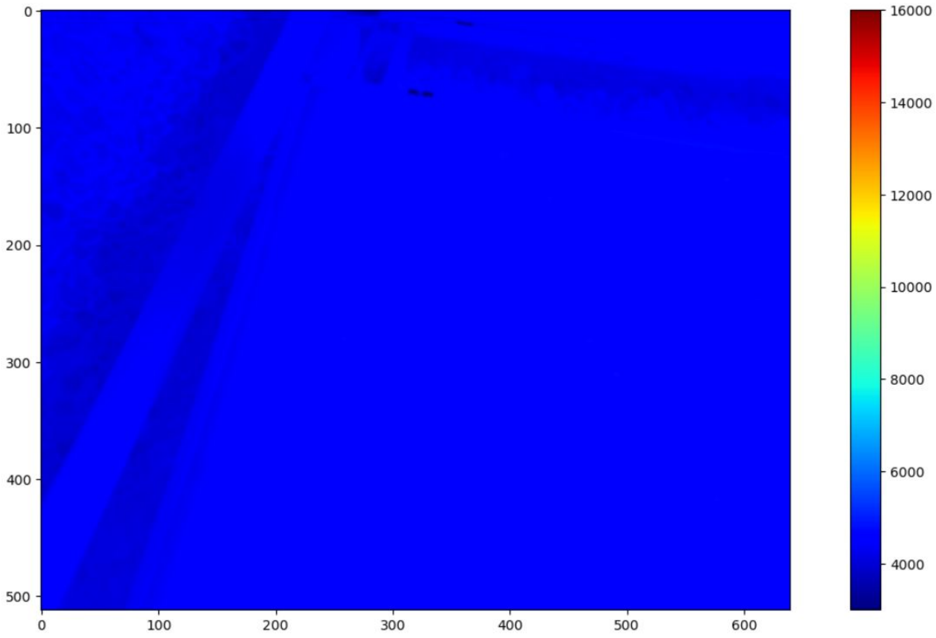
Range: 3000 - 4750



Dataset 1, img 4

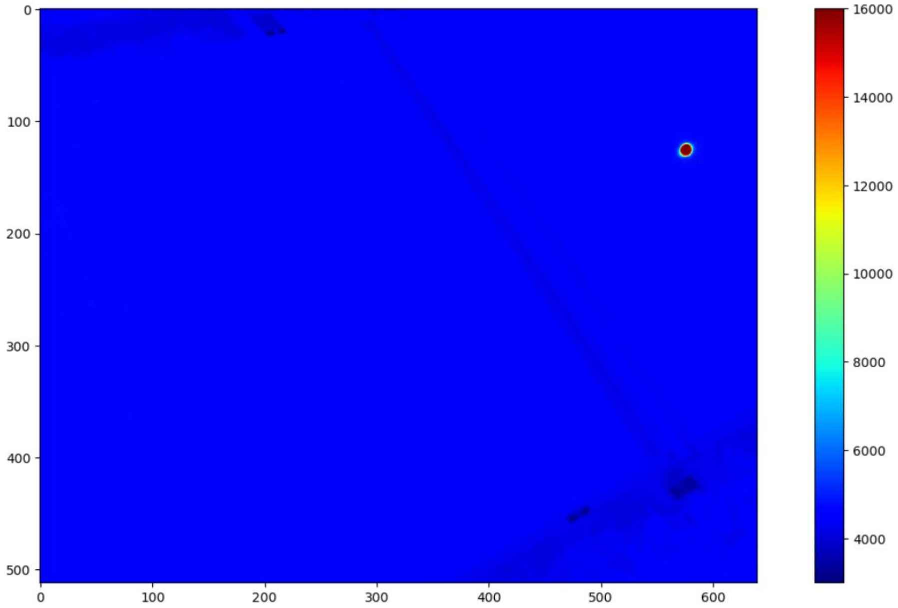
Range: 4000 - 16000

Optimal Map Range Selection: All Inclusive



Dataset 1, img 1

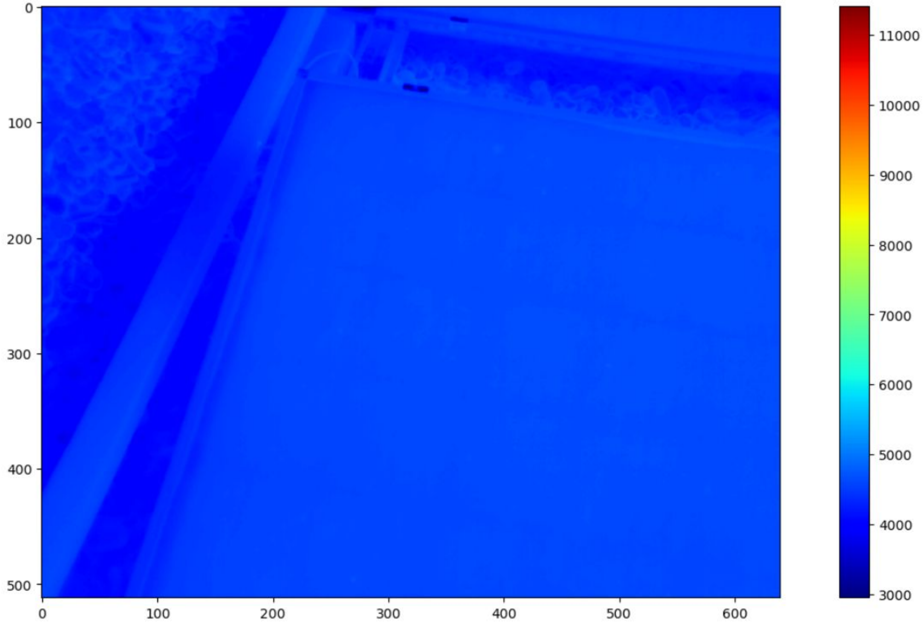
Range: 3000 - 1600



Dataset 1, img 4

Range: 3000 - 16000

Optimal Map Range Selection: Averaging

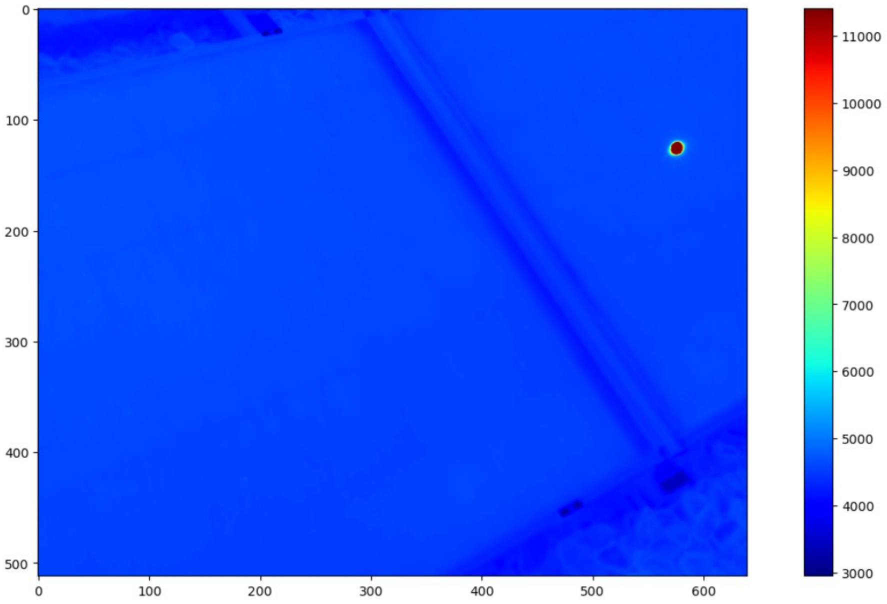


Dataset 1, img 4

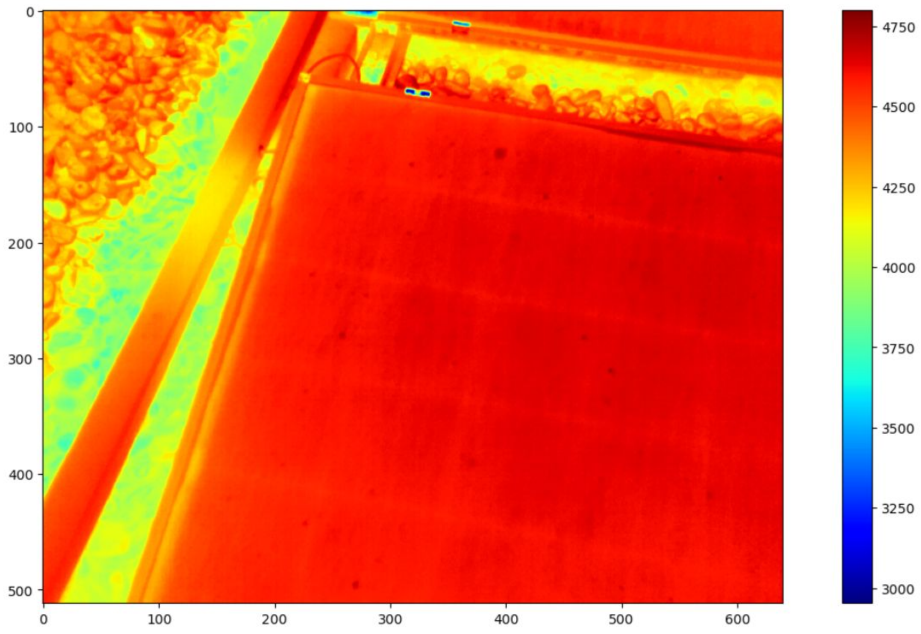
Range: 2953 - 11407

Dataset 1, img 1

Range: 2953 - 11407



Optimal Map Range Selection: Disregarding Abnormality

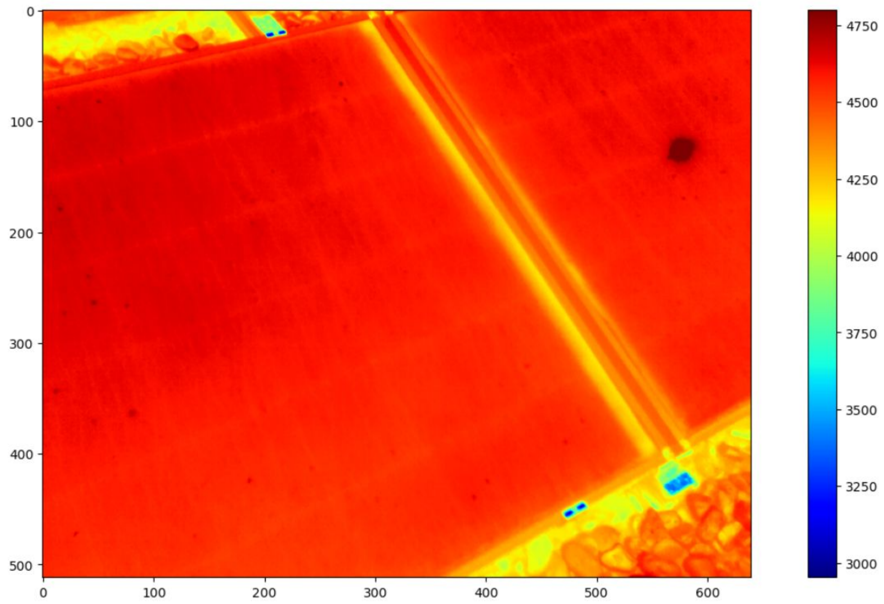


Dataset 1, img 4

Range: 2953 - 4800

Dataset 1, img 1

Range: 2953 - 4800



Evaluation

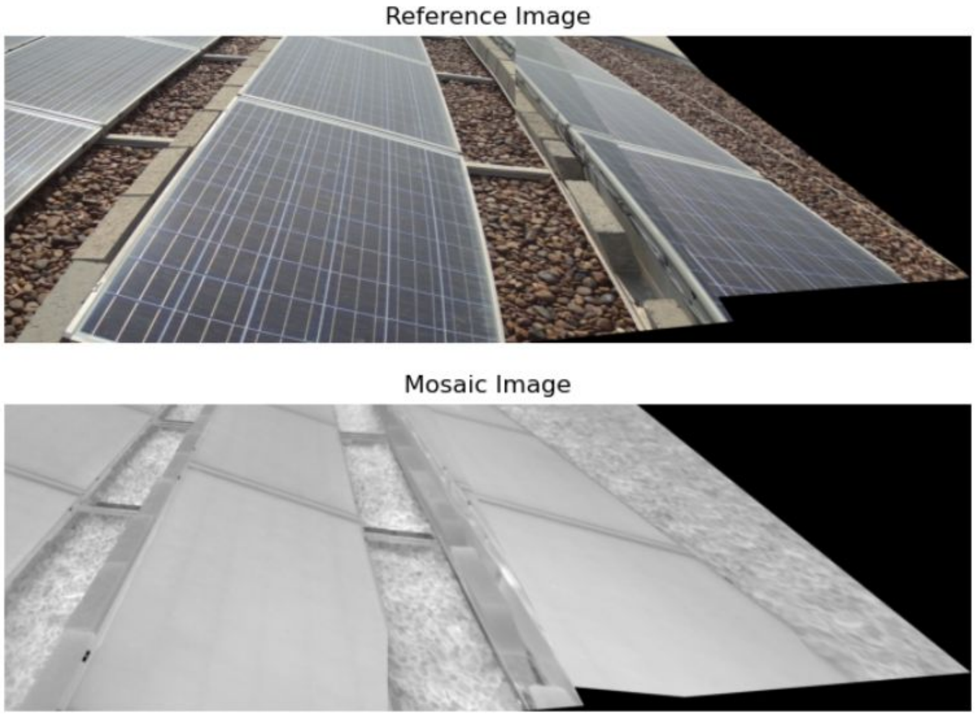
Evaluation Pipeline

Notebook can be found here.

Metrics include:

- Entropy
- Clarity via sobel matrices
- Registration Error (done in the stitching pipeline over several iterations)
- PSNR
- SSIM
- Mutual Information (MI)

```
Entropy: 5.690297133230913
Clarity (ClaritySobel8): 16.962398826547833
PSNR: 28.625760725788446
SSIM: 0.344822545718582
Mutual Information: 0.3685213722618679
```



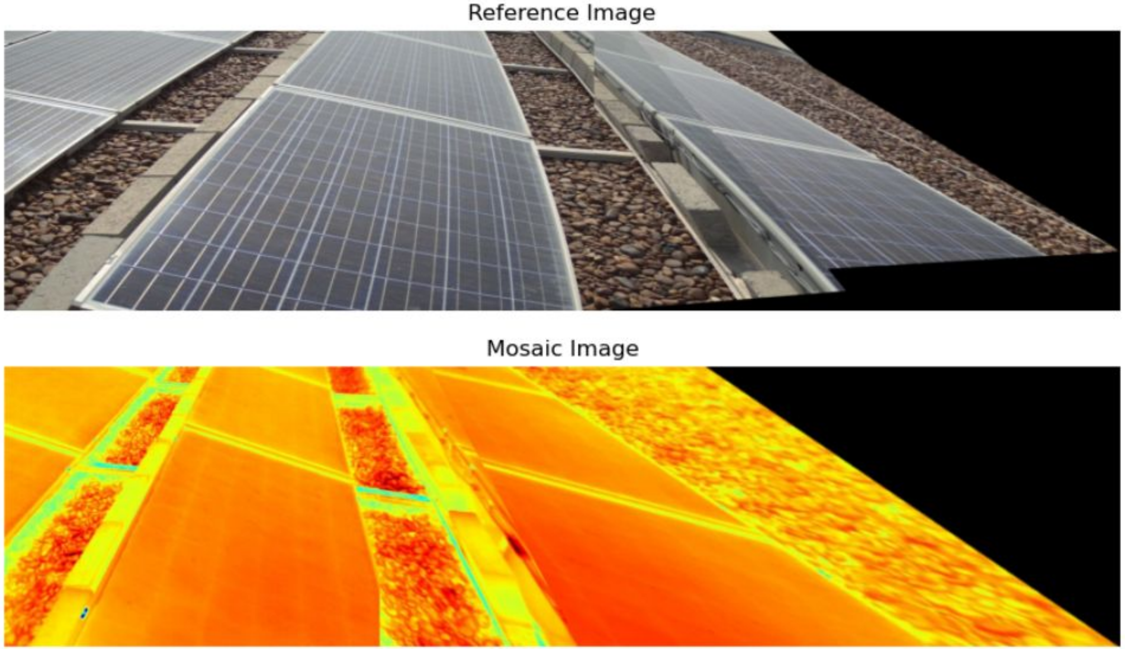
Evaluation Pipeline

Notebook can be found [here](#).

Metrics include:

- Entropy
- Clarity via sobel matrices
- Registration Error (done in the stitching pipeline over several iterations)
- PSNR
- SSIM
- Mutual Information (MI)

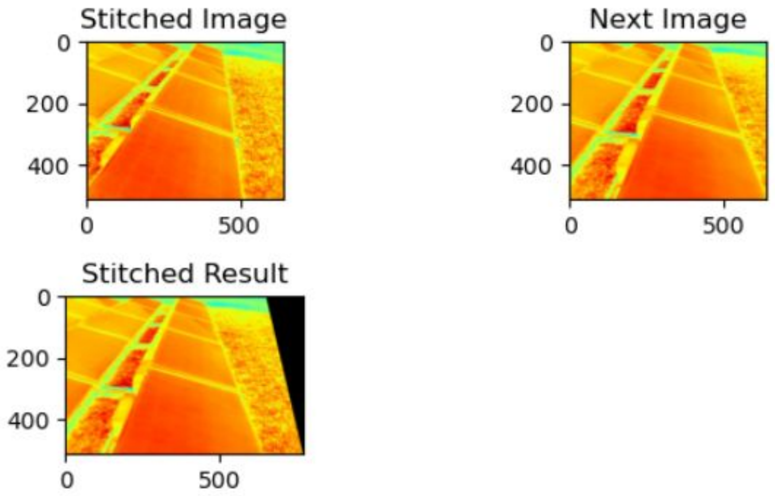
```
Entropy: 6.457833486119051
Clarity (ClaritySobel8): 24.928210759261987
PSNR: 28.65812459144219
SSIM: 0.3271906082548263
Mutual Information: 0.10127490507661438
```



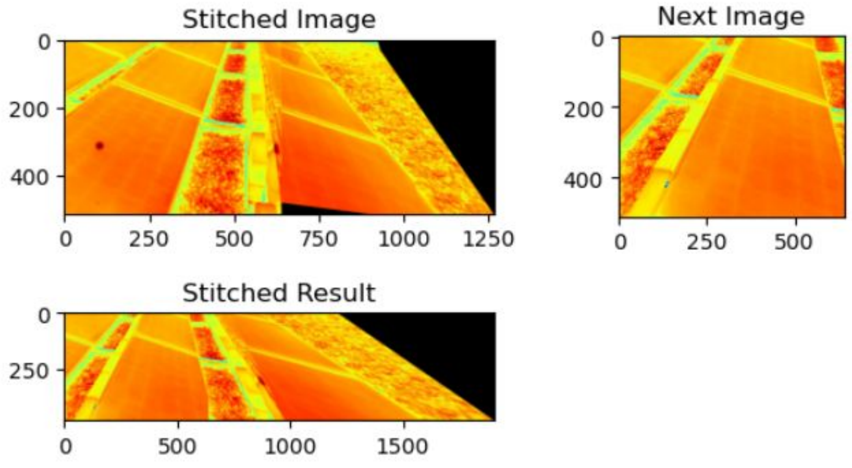
Evaluation Pipeline

Registration Error is calculated throughout the stitching process then averaged to get an overall value for the mosaic.

Registration Error (RMSE): 75.66826629638672
Time for execution: 0.2374636000022292



Registration Error (RMSE): 635.7080688476562
Time for execution: 0.36569760006386787



Overall Registration Error (Average RMSE): 279.38543701171875

To-Do Next

- Automate evaluation such that we can evaluate changes to the stitching pipeline
  - Evaluate with pairs of images
  - Run with all possible pairs
  - Aggregate to one value for pipeline version & save in a table
- Pipeline challenges
  - Shadows [skip - manual marking]
  - Sun flares [bouncing box & disregard when picking range]
  - Low variability of color maps
- Color map range
  - Specific to each image (some variation is okay)
  - Remove hot spots
  - BF + line detection
  - Zero-in on most common temperatures
- Compare same metrics with other pipelines & softwares

Meeting 10/06/2024

Agenda

- Research Follow-Up:
  - Infrared Image Stitching for Wind Turbine Blades
  - RMSE
- Software Experimentation:
  - PTGui
  - AutoStitch
  - Hugin
  - Others (Pix4Dmapper, FLIR Thermal Studio, NISwGSP)

Research Follow-Up

<u>Paper</u>: An Infrared Image Stitching Method for Wind Turbine Blade Using UAV Flight Data and U-Net, Yu et al.

<u>Paper's motivation</u>: Propose an image stitching pipeline specific to wind turbine blades.

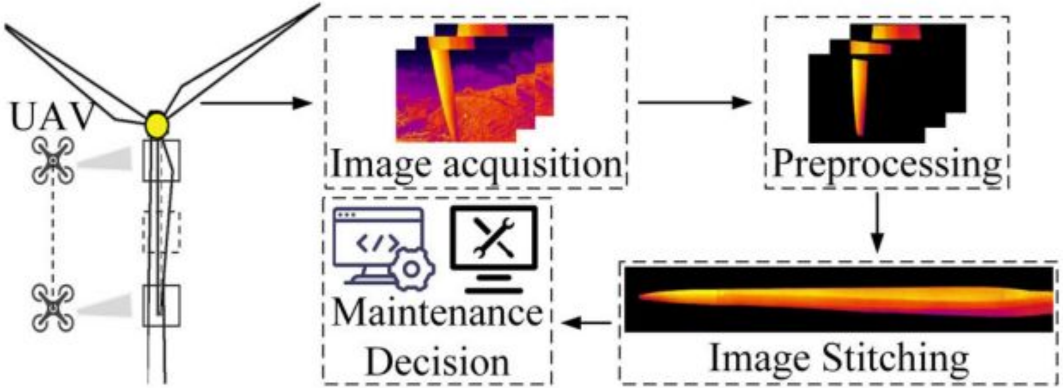


Fig. 1. Automatic inspection of wind turbine blade based on UAV.

Research Follow-Up

Background removal is done to isolate the turbine blade. Stitching is then done via calculating:

1. Rotation parameter
2. Translation parameter
3. Scaling parameter

As opposed to feature detection.

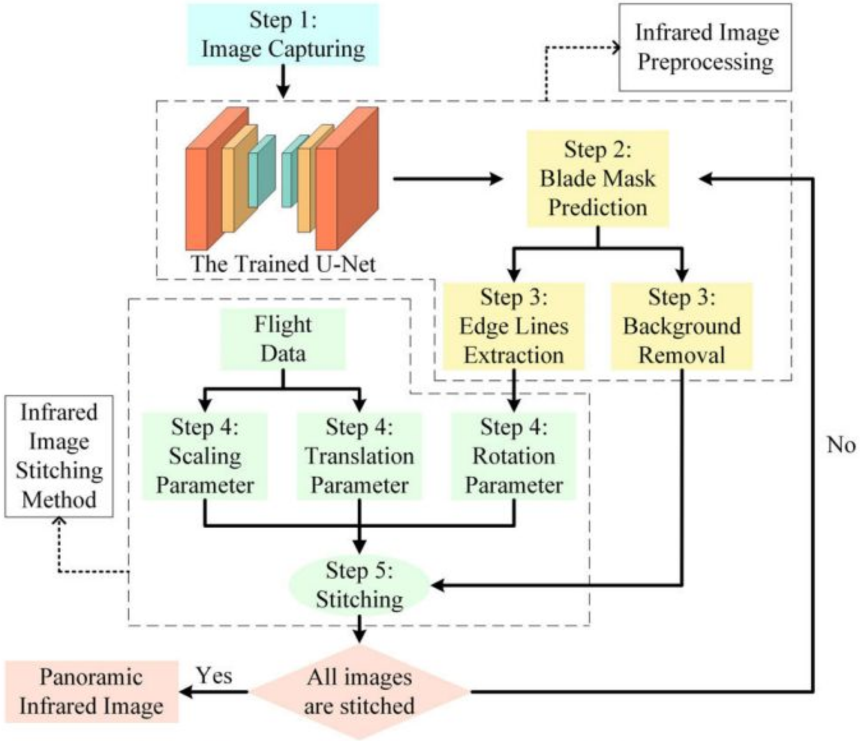


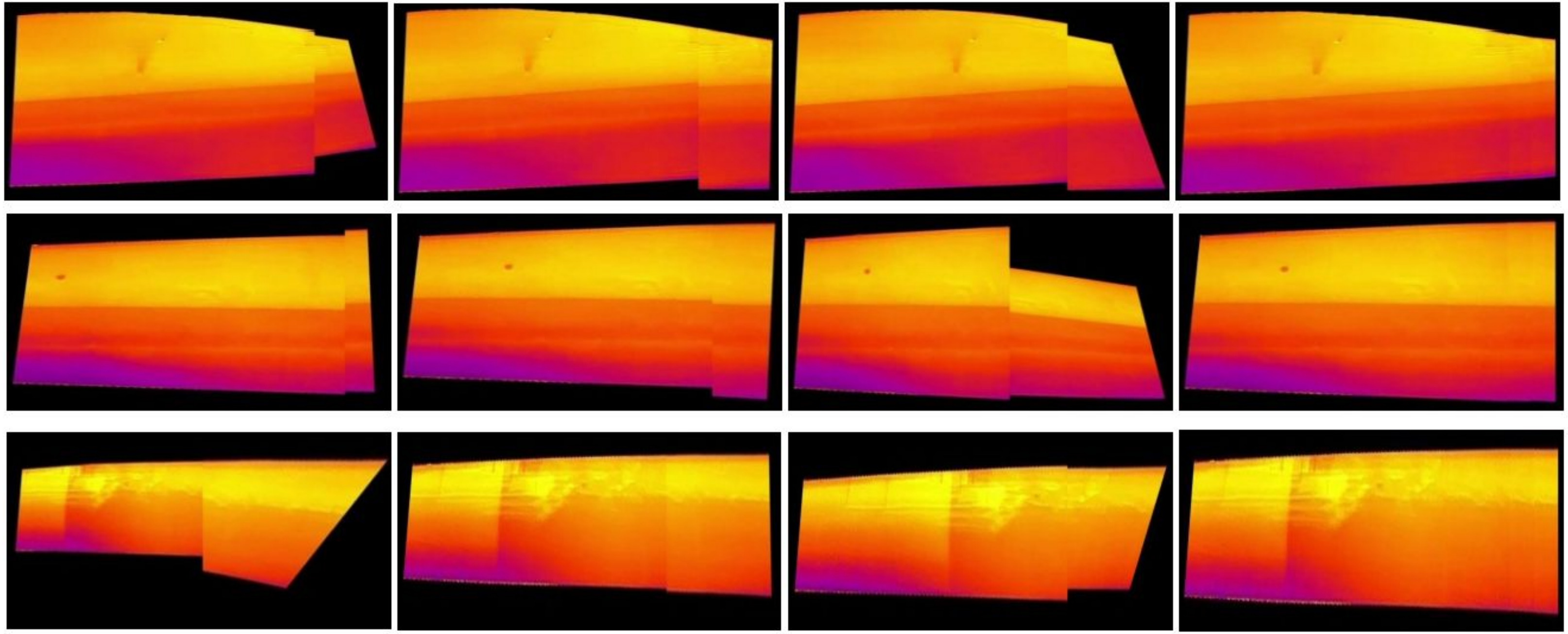
Fig. 2. Framework of the proposed method.

Research Follow-Up

Blade Root Area

Blade Middle Area

Blade Tip Area



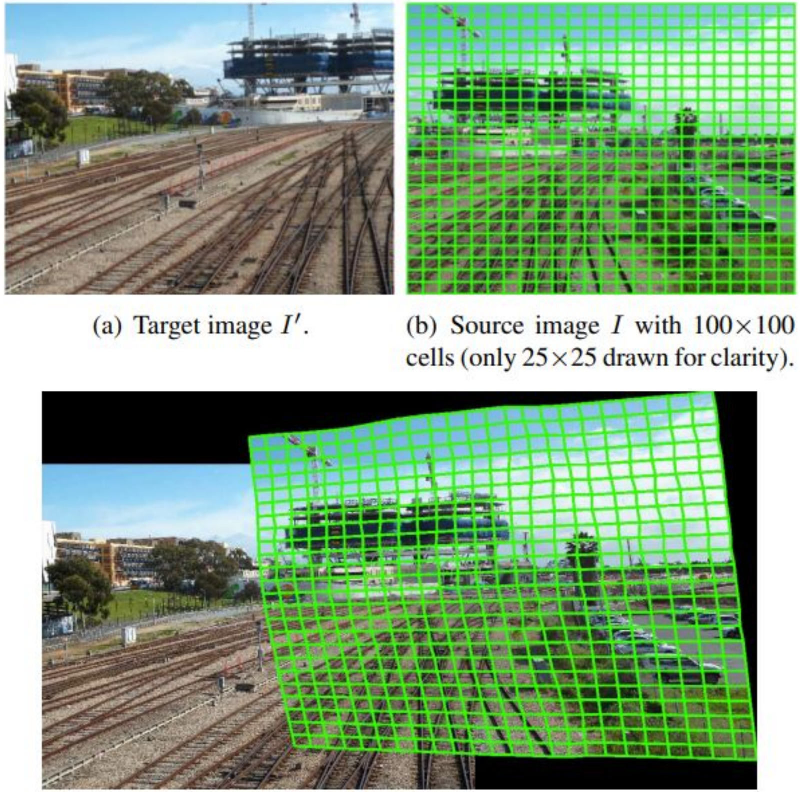
(a) (b) (c) (d)

Fig. 13. Comparison of image stitching results when blade B is in the shade. (a) Stitching results based on SIFT algorithm. (b) Stitching results based on SURF algorithm. (c) Stitching results based on ORB algorithm. (d) Stitching results based on the proposed algorithm.

Research Follow-Up

Paper: As-Objective-As-Possible Image Stitching with Moving DLT, Zaragoza et al.

Paper's motivation: propose warps that aim to be globally projective, yet allow local non-projective deviations to account for violations to the assumed imaging conditions.



(a) Target image I'.

(b) Source image I with 100×100 cells (only 25×25 drawn for clarity).

(c) Aligned images with transformed cells overlaid to visualise the warp. Observe that the warp is globally projective for extrapolation, but adapts flexibly in the overlap region for better alignment.

Research Follow-Up

Quantitative Evaluation:

RMSE done on pairs of keypoint matches.

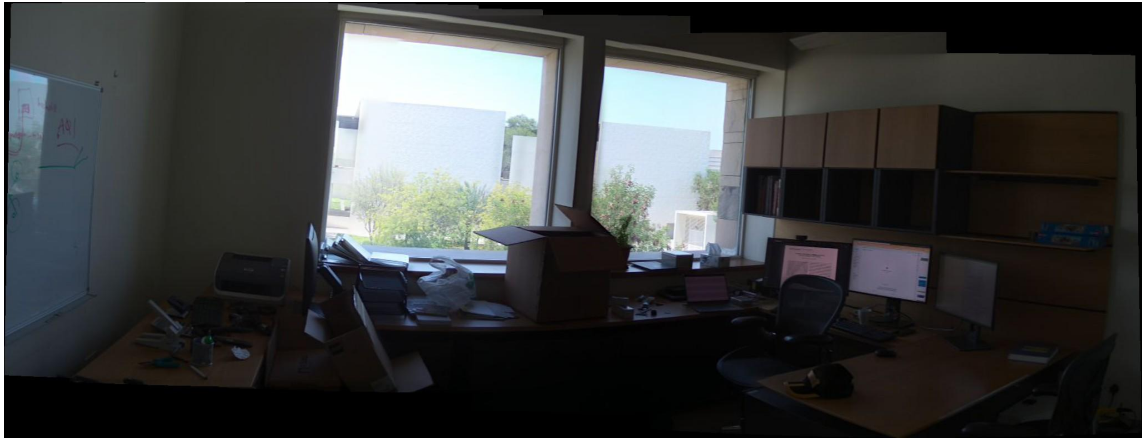
Supplementary material was promised but I could not locate a working link.

Let $\mathbf{x} = [x\ y]^T$ and $\mathbf{x}' = [x'\ y']^T$ be matching points across overlapping images I and I'.

To quantify the alignment accuracy of an estimated warp $f : \mathbb{R}^2 \mapsto \mathbb{R}^2$, we compute the root mean squared error (RMSE) of f on a set of keypoint matches $\{\mathbf{x}_i, \mathbf{x}'_i\}_{i=1}^{N}$, i.e., $\text{RMSE}(f) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \|f(\mathbf{x}_i) - \mathbf{x}'_i\|^2}$.

Software Experimentation: Datasets

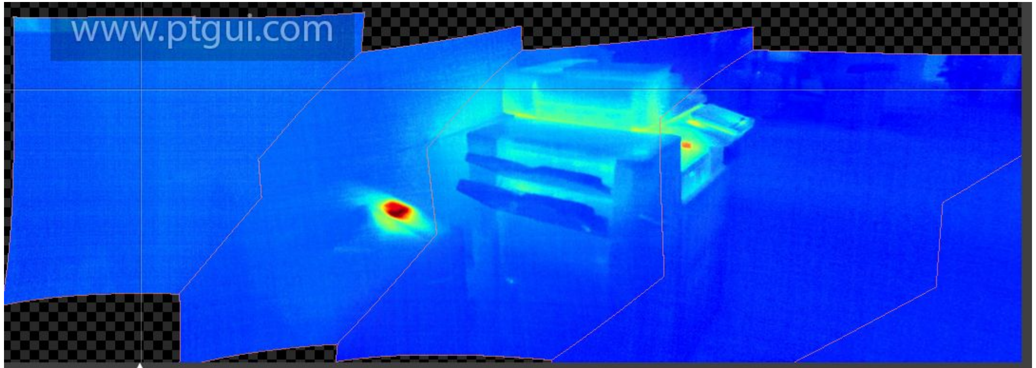
RGB versions (.jpg)

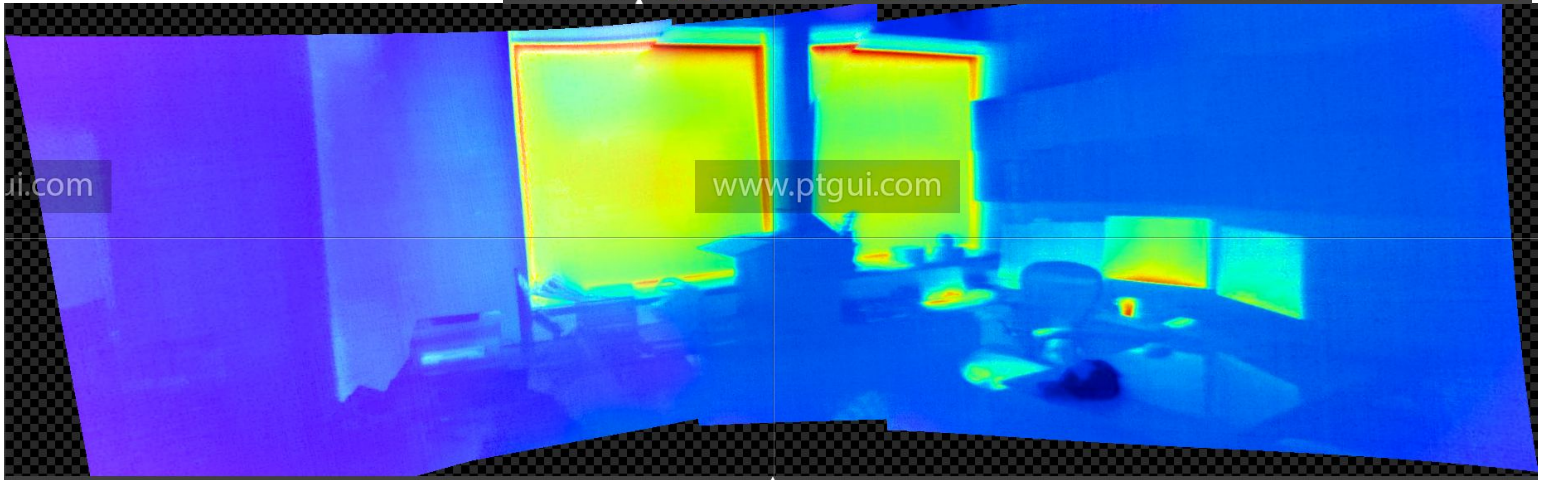


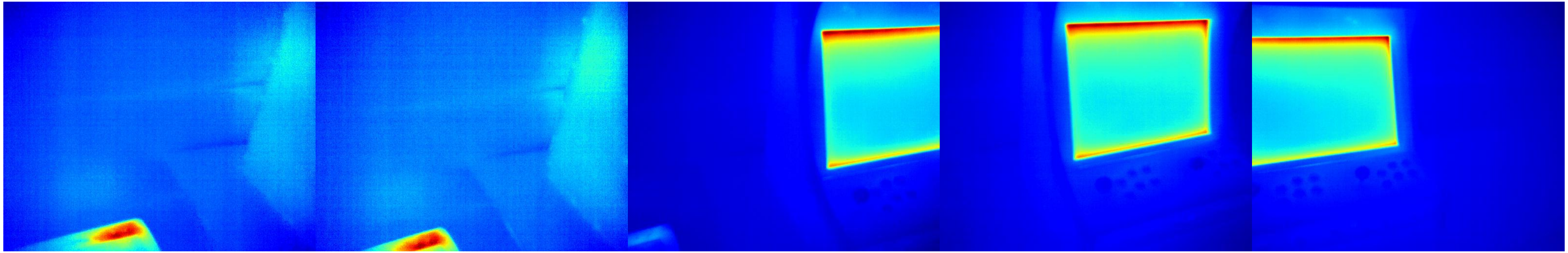
Software Experimentation: Datasets

Color-mapped versions (.jpg)

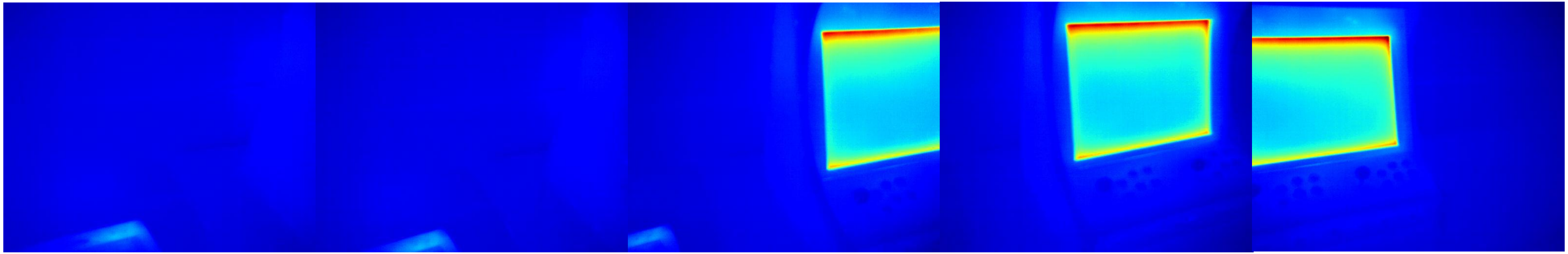
Uniforming thermal range lead to significant loss of detail



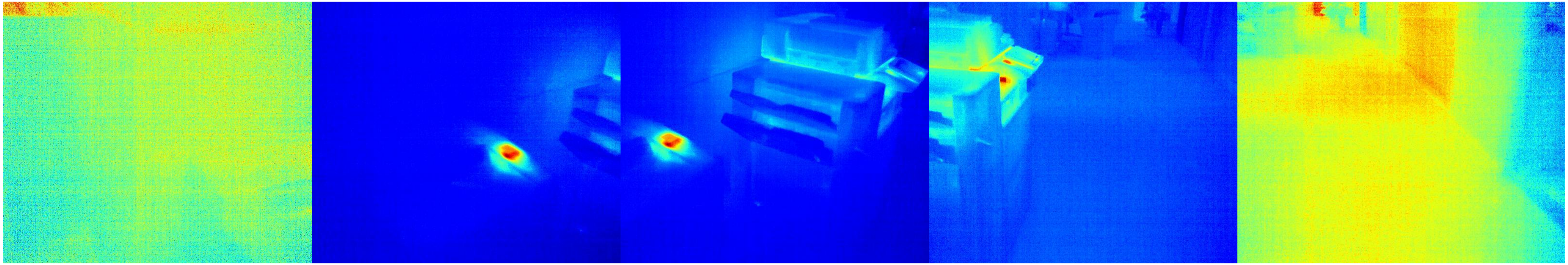




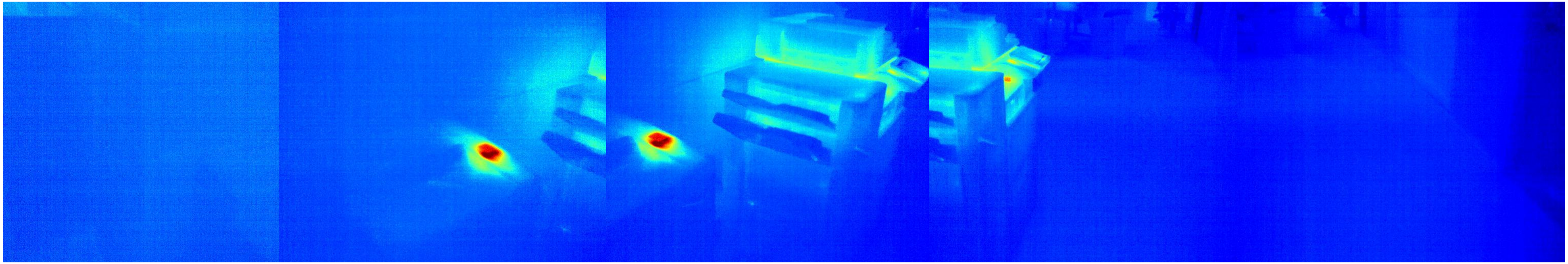
Optimal color map



Uniform color map



Optimal color map



Uniform color map

Software Experimentation: Datasets

Thermal versions (.tif)

AutoStitch accepted the input but crashed repeatedly.

PTGui accepted the input, but evaluation can’t be done without image save which is lacking in the demo version.

Hugin accepted the input. Results are shown.

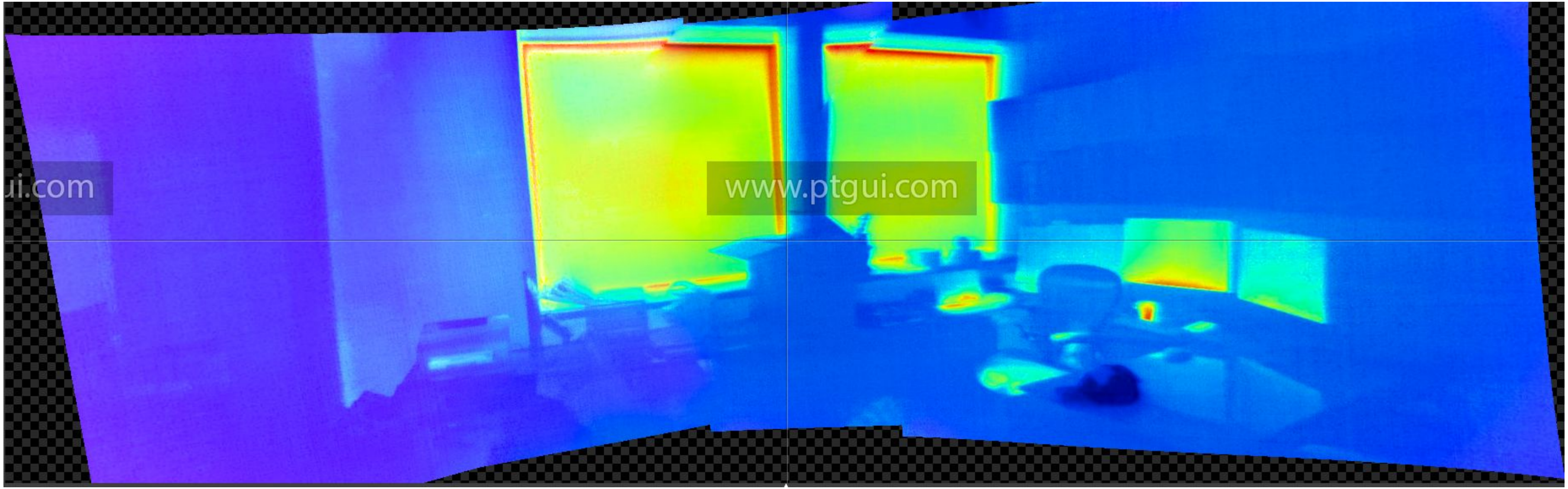
PTGui

PTGui: RGB

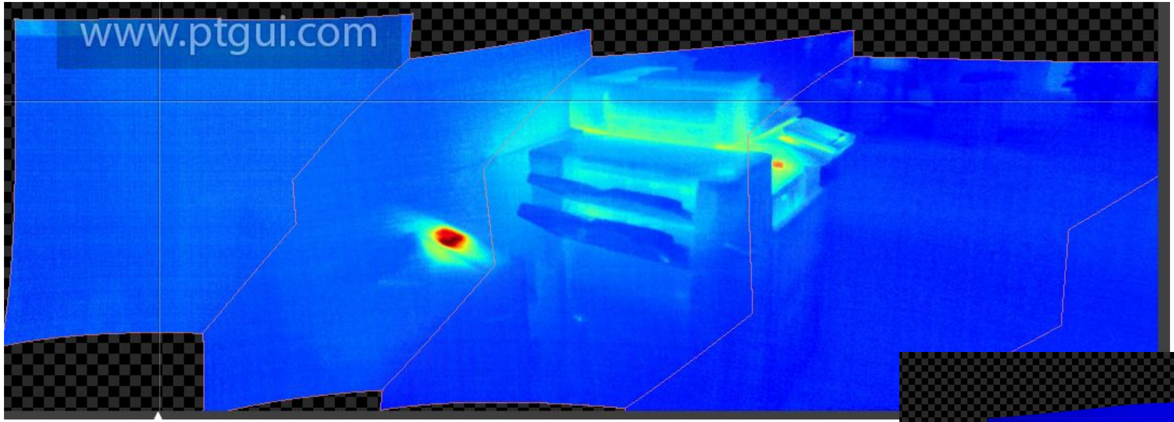
PTGui: RGB

PTGui: Color-Mapped Thermal

Dataset 1: stitched normally. Less than ideal results.



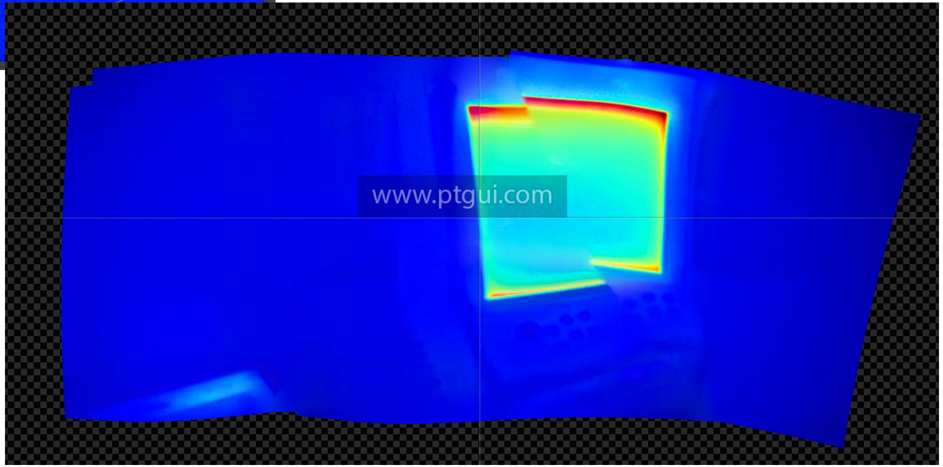
PTGui: Color-Mapped Thermal



Datasets 2 & 3:

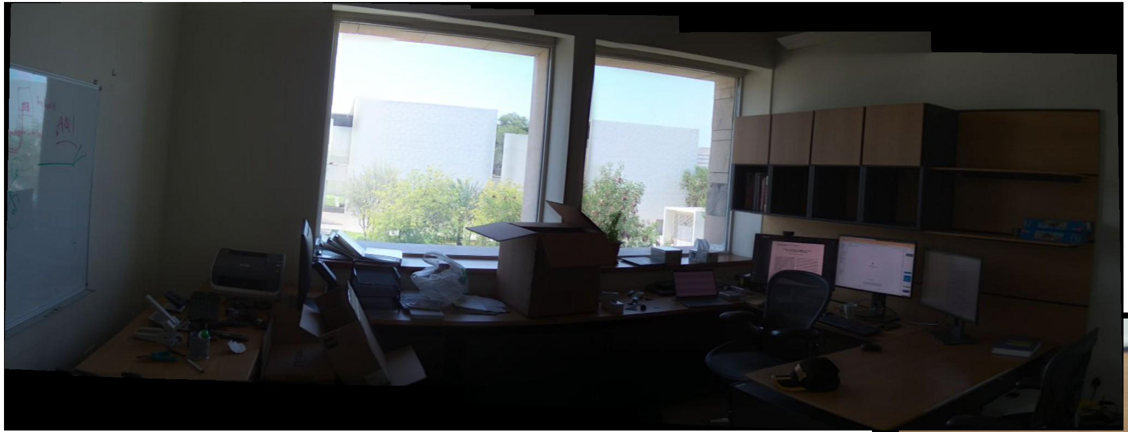
Both required manual CPs be added.

Results after manual addition.



AutoStitch

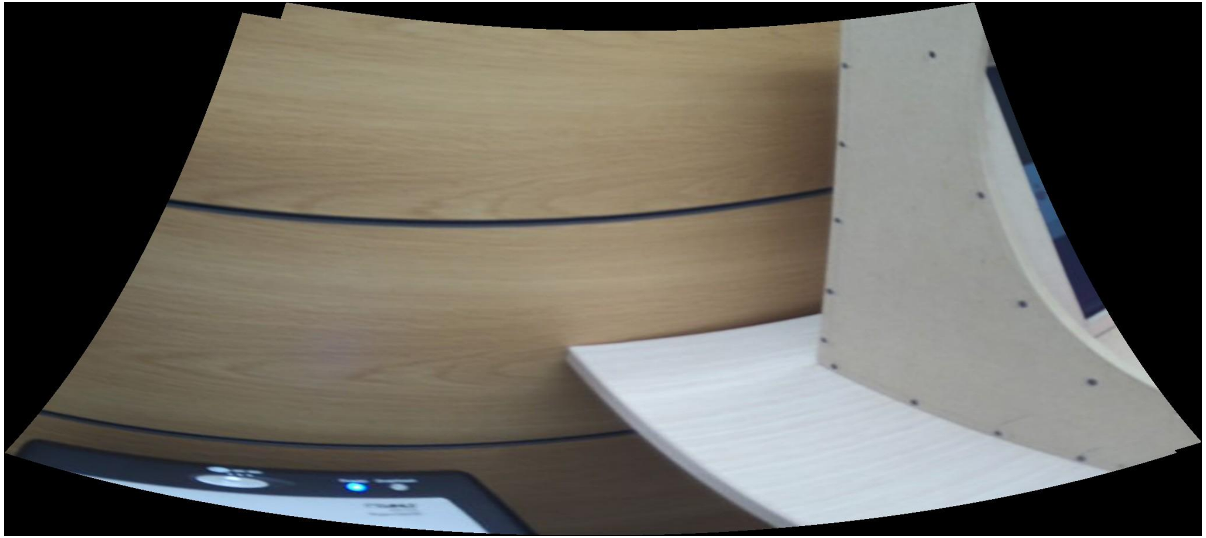
AutoStitch: RGB



AutoStitch: RGB

Dataset 3:

Very distorted. Much of the mosaic has been omitted.



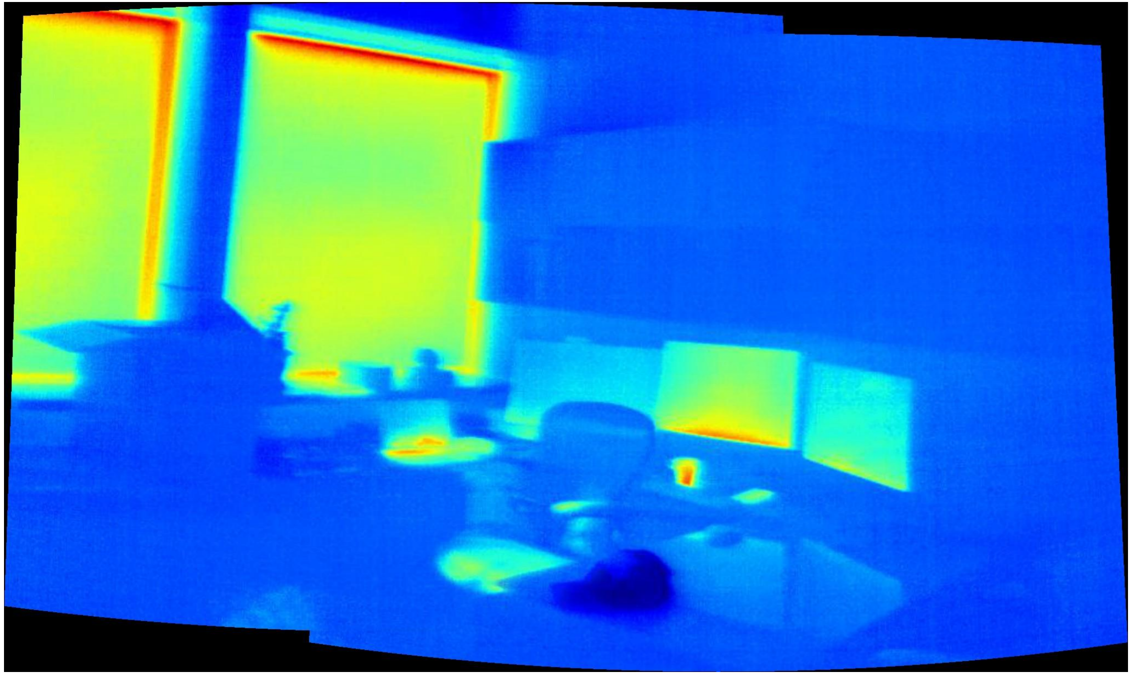
AutoStitch: Color-Mapped Thermal

Dataset 1:

much of the mosaic has been omitted.

Datasets 2 & 3:

failed to stitch (likely lack of overlap: “failed to align”)



Hugin

Hugin: RGB

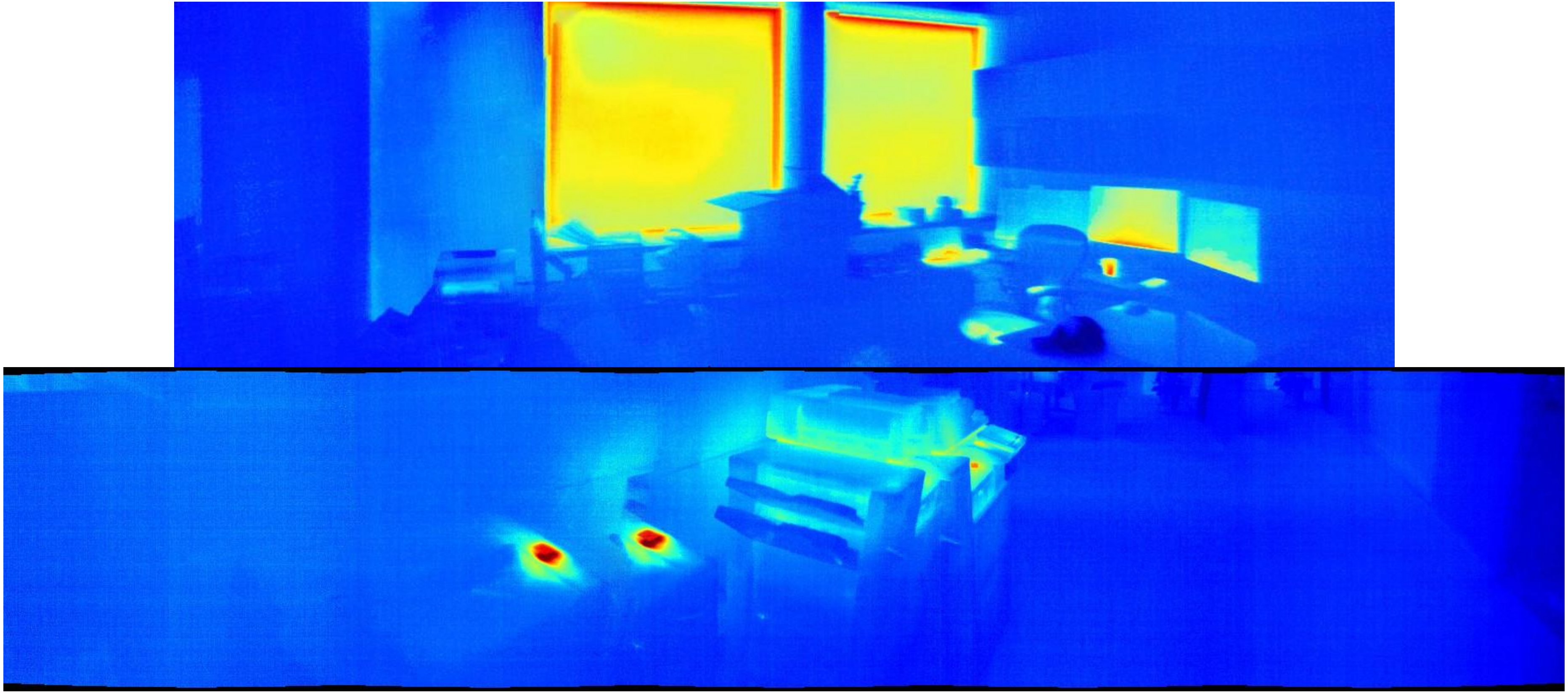
Some of the best RGB results, for dataset 2 especially.

Hugin: RGB

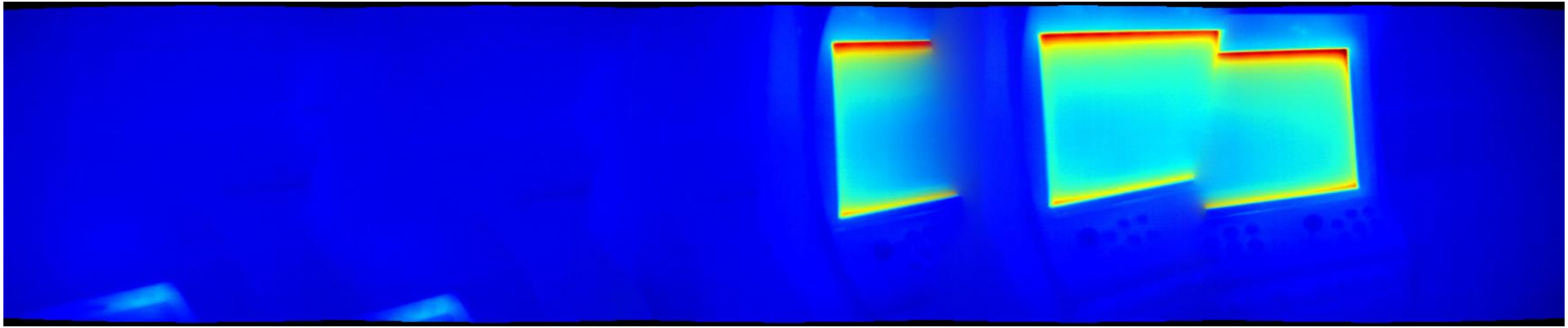
Dataset 3 required manual CPs be added, likely due to excessive blurriness.

Result after manual addition. Much of the mosaic has been omitted.

Hugin: Color-Mapped Thermal



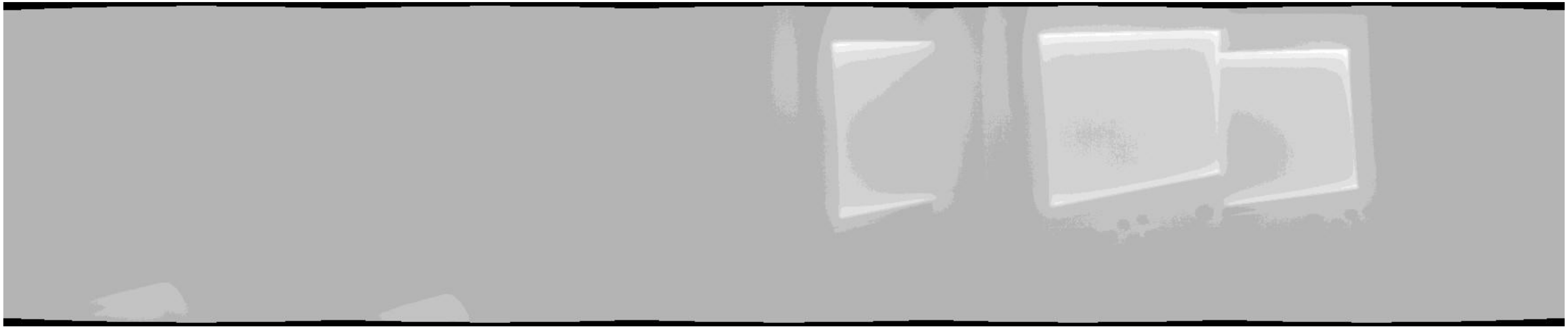
Hugin: Color-Mapped Thermal

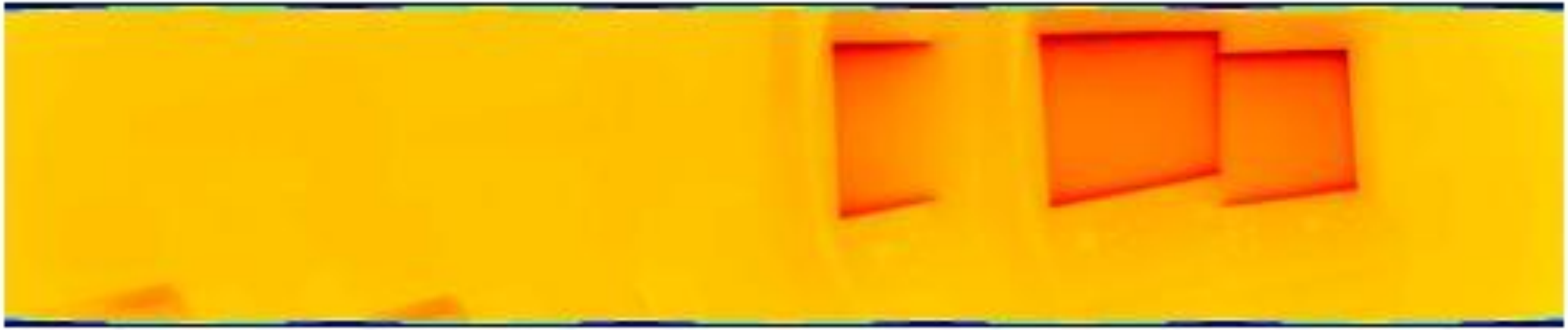


Hugin: Thermal

Hugin: Thermal

Hugin: Thermal





Others

Softwares not covered

Pix4Dmapper

FLIR Thermal Studio

- Extremely limited trial version
- Panorama feature limited to Pro version

NISwGSP

- From this paper

To-Do Next

- Check if Hugin can stitch thermals
- Try different color maps
- Brainstorm ideas for initial stitching pipeline
  - Extracting features from different color maps & using all

- Evaluation of mosaicing approaches (RMSE, …)
  - RGBs as GT; images with overlap
  - Single thermal image – synthetic mosaicing
    - Mimicking distortions (movement)

Meeting
03/06/2024

Agenda

- Ground Truth & Evaluation in Thermal Mosaicing
- Thermal Mosaicing Softwares

Ground Truth & Evaluation in Thermal Mosaicing

Paper: Robust UAV Thermal Infrared Remote Sending Images Stitching Via Overlap-Prior-Based Global Similarity Prior model, Cui et al.

Paper's motivation: Propose a novel method for stitching large-scale thermal infrared remote sensing (TIRS) images obtained from UAVs to produce high-quality panoramic images.

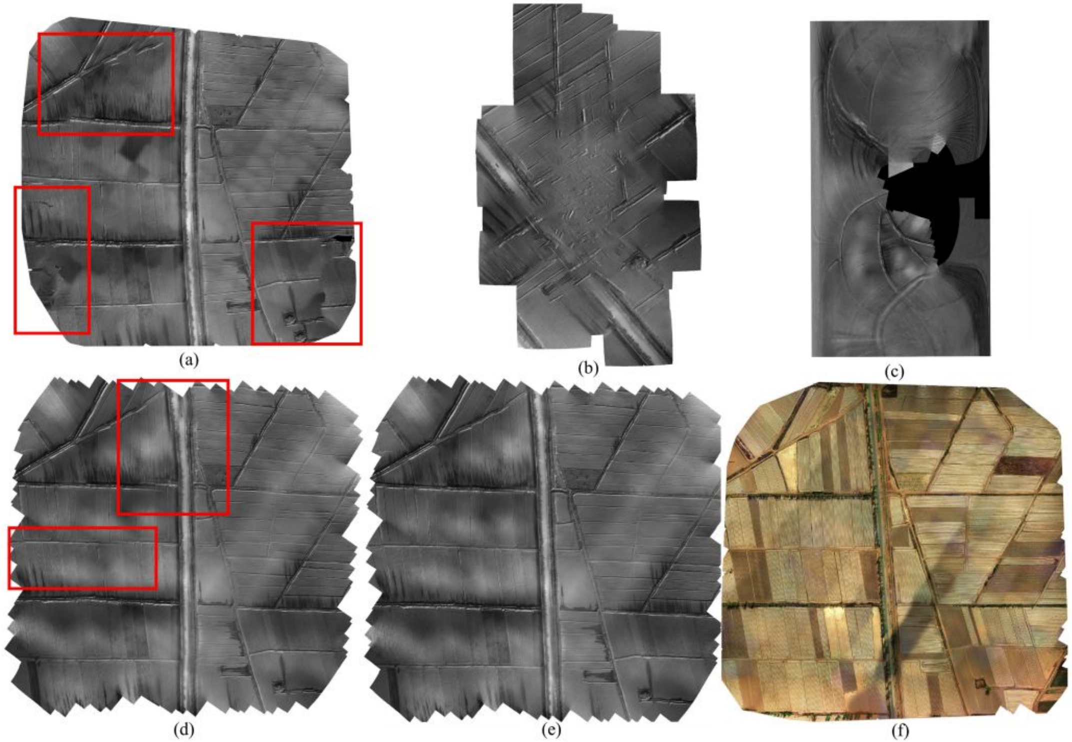


Fig. 6. Stitched result of Field 2 on the afternoon of May 1, 2018 in cloudy weather (284 images with 70% front image overlap). The red boxes indicate the mosaic dislocation and distortion. (a) Pix4Dmapper. (b) PTGui. (c) AutoStitch. (d) Original GSP. (e) OP-GSP. (f) Visible image of study area.

Ground Truth & Evaluation in Thermal Mosaicing

Dataset & GT:

The study area consists of four fields which range from 150,000 to 250,000 m^2.

Ground Truth is taken to be the **visible mosaic** created via Pix4Dmapper of the same study area.

“Comparison with the visible panoramic images of the study area (result from Pix4Dmapper) in the same period [see Figs. 6(f) and 7(f)], it can be found that …”

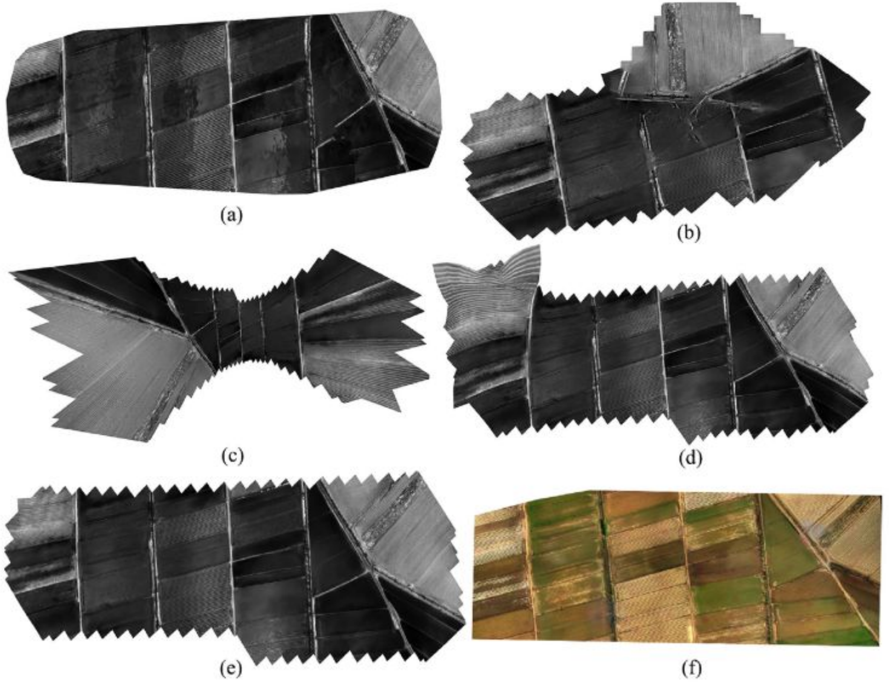


Fig. 1. Image stitching illustration of 100 UAV TIRS images. (a) Pix4Dmapper. (b) PTGui. (c) AutoStitch. (d) Original GSP. (e) Ours. (f) Visible image of study area.

Ground Truth & Evaluation in Thermal Mosaicing

Evaluation & Metrics:

Did both qualitative and quantitative evaluation.

In terms of quantitative, RMSE is used as a metric to compare GSP and OP-GSP.

TABLE III
EVALUATION AND COMPARISONS OF STITCHING RESULTS ON 12 GROUPS OF UAV TIRS IMAGES IN 2018

Experimental Environment				Pix4Dmapper	PTGui	AutoStitch	GSP	OP-GSP (Ours)
fine	morning May	*Field 4*	**-Result**	Holes	Dislocation	Distortion	Dislocation	Success
			-RMSE	—	—	—	1.90883	**0.866687**
	morning July	*Field 4*	**-Result**	Success	Success	Distortion	Dislocation	Success
			-RMSE	—	—	—	1.32339	**0.677089**
	noon May	*Field 3*	**-Result**	Success	Dislocation	Distortion	Dislocation	Success
			-RMSE	—	—	—	1.44841	**0.767659**
cloudy	morning July	*Field 2*	**-Result**	Dislocation	Dislocation	Distortion	Dislocation	Success
			-RMSE	—	—	—	1.53082	**0.72491**
	morning July	*Field 3*	**-Result**	Failed	Dislocation	Distortion	Dislocation	Success
			-RMSE		—	—	2.1054	**0.752048**
	afternoon May	*Field 1*	**-Result**	Dislocation	Distortion	Distortion	Dislocation	Success
			-RMSE	—	—	—	1.55952	**0.954643**
	afternoon July	*Field 1*	**-Result**	Failed	Dislocation	Distortion	Dislocation	Success
			-RMSE		—	—	1.74037	**0.918486**
	afternoon May	*Field 2*	**-Result**	Dislocation	Distortion	Distortion	Dislocation	Success
			-RMSE	—	—	—	1.77413	**0.814871**
light rain	morning Sep	*Field 1*	**-Result**	Dislocation	Dislocation	Distortion	Dislocation	Success
			-RMSE	—	—	—	1.45784	**0.869685**
	morning Sep	*Field 3*	**-Result**	Dislocation	Dislocation	Distortion	Dislocation	Success
			-RMSE	—	—	—	2.17742	**0.86588**
	afternoon Sep	*Field 2*	**-Result**	Dislocation	Dislocation	Distortion	Success	Success
			-RMSE	—	—	—	1.12346	**0.916767**
	afternoon Sep	*Field 4*	**-Result**	Failed	Success	Distortion	Dislocation	Success
			-RMSE		—	—	1.3577	**0.771898**

Note: Dislocation indicates that there are only a few minor stitching misalignments in the result and can keep the basic structure of the image [such as Fig. 6(a)]. Distortion indicates that the image stitching result has serious deformation and cannot maintain the original structure [such as Fig. 6(c)]. Holes means some information is lost inside the image, but no dislocation and distortion occurred. Success indicates good stitching result [such as Fig. 6(e)]. In addition, the vegetation coverage was low in May and high in September.

Ground Truth & Evaluation in Thermal Mosaicing

Paper: A Novel Stitching Method for High-Precision Low-Overlap Thermal Infrared Array Sweeping Images, Jin et al.

Paper's motivation: proposes a novel stitching method for high-precision, low-overlap thermal infrared array scanning (TIRAS) images.

Evaluation:

> Compared the image coordinates of the geometric targets with the corresponding UTM projection coordinates using RMSE.

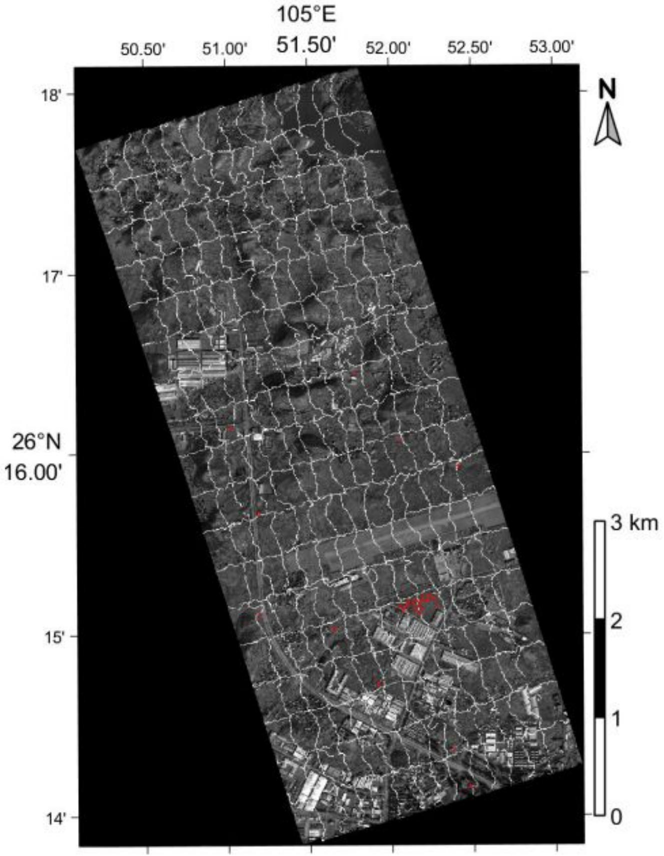
$$\begin{bmatrix} \boldsymbol{U}_3 \\ \boldsymbol{V}_3 \\ \boldsymbol{K}_3 \end{bmatrix} = \boldsymbol{H}_3 \times \begin{bmatrix} \boldsymbol{P}_{\boldsymbol{I}}^{T} \\ \mathbf{1} \end{bmatrix} \tag{21}$$

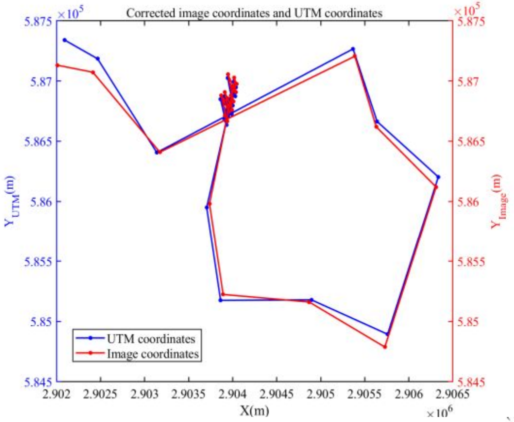
$$\begin{bmatrix} \boldsymbol{x'}_{\boldsymbol{I}} \\ \boldsymbol{y'}_{\boldsymbol{I}} \end{bmatrix} = \begin{bmatrix} (\boldsymbol{U}_2./\boldsymbol{K}_2)^{T} \\ (\boldsymbol{V}_2./\boldsymbol{K}_2)^{T} \end{bmatrix} \tag{22}$$

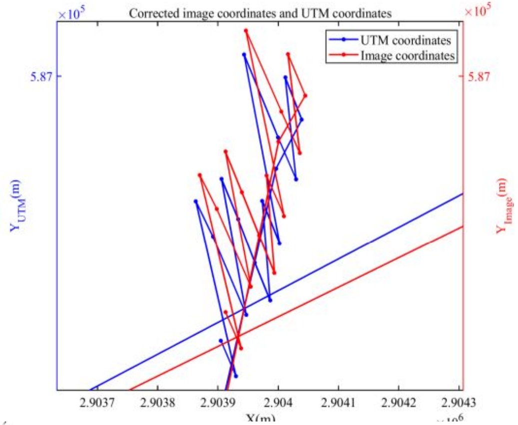
$$\mathrm{RMSE} = \sqrt{\left(\sum_{v=1}^{N} \left(x'^{I}_{v} - x^{G}_{v}\right)^2 + \left(y'^{I}_{v} - y^{G}_{v}\right)^2 \right) \Big/ N} \tag{23}$$

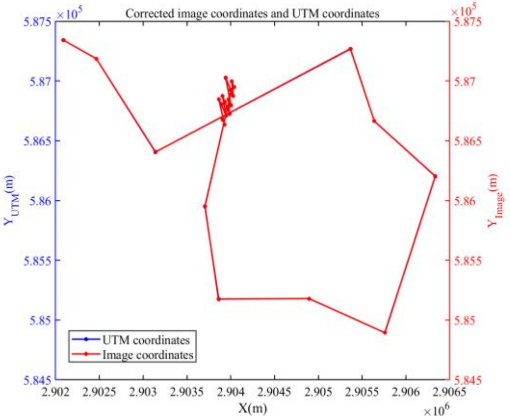
where $(\boldsymbol{U}_3, \boldsymbol{V}_3, \boldsymbol{K}_3)$ denote the spatial auxiliary coordinate matrices of the image coordinate matrix $\boldsymbol{P}_{\boldsymbol{I}}$ corrected by the homography matrix $\boldsymbol{H}_3$. $(\boldsymbol{x'}_{\boldsymbol{I}}, \boldsymbol{y'}_{\boldsymbol{I}})$ represents the image coordinate matrices of the mosaic image coordinate matrix $\boldsymbol{P}_{\boldsymbol{I}}^{T}$ corrected by the homography matrix $\boldsymbol{H}_3$. RMSE denotes the RMSE between the corrected image coordinates $(\boldsymbol{x}'_{\boldsymbol{I}}, \boldsymbol{y}'_{\boldsymbol{I}})$ and the corresponding UTM projected coordinates $\boldsymbol{P}_{\boldsymbol{G}}$. N represents the number of geometric target coordinates.

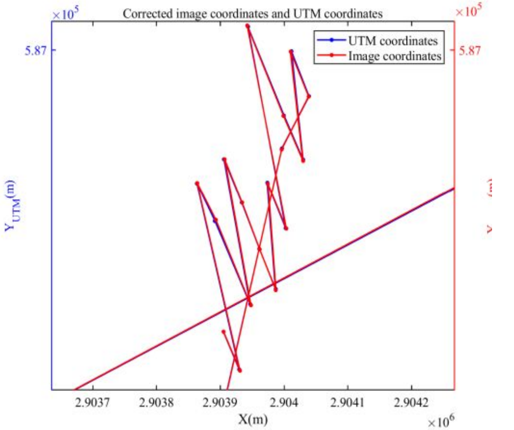
Ground Truth & Evaluation in Thermal Mosaicing











Ground Truth & Evaluation in Thermal Mosaicing

Paper: Rapid Mosaicking of Unmanned Aerial Vehicle (UAV) Images for Crop Growth Monitoring Using the SIFT Algorithm, Zhao et al.

Paper's motivation: Propose a rapid mosaicking method based on scale-invariant feature transform (SIFT) for mosaicking UAV images used for crop growth monitoring.

Evaluation: Used the SSIM index on overlapping parts of the mosaic and original images.

remote sensing

MDPI

Article

Rapid Mosaicking of Unmanned Aerial Vehicle (UAV) Images for Crop Growth Monitoring Using the SIFT Algorithm

Jianqing Zhao †, Xiaohu Zhang †, Chenxi Gao, Xiaolei Qiu, Yongchao Tian, Yan Zhu and Weixing Cao *

National Engineering and Technology Center for Information Agriculture, Key Laboratory for Crop System Analysis and Decision Making, Ministry of Agriculture and Rural Affairs, PRC, Jiangsu Key Laboratory for Information Agriculture, Jiangsu Collaborative Innovation Center for Modern Crop Production, Nanjing Agricultural University,1 Weigang Road Nanjing, Jiangsu 210095, China; jianqingz@hotmail.com (J.Z.); zhangxiaohu@njau.edu.cn (X.Z.); gaochenxi_@hotmail.com (C.G.); qiuxiaolei@njau.edu.cn (X.Q.); yctian@njau.edu.cn (Y.T.); yanzhu@njau.edu.cn (Y.Z.)

* Correspondences: caow@njau.edu.cn

† Jianqing Zhao and Xiaohu Zhang have contributed to the work equally.

Received: 15 April 2019; Accepted: 21 May 2019; Published: 23 May 2019

check for updates

Ground Truth & Evaluation in Thermal Mosaicing

Paper: A Novel Adjustment Model for Mosaicking Low-Overlap Sweeping Images, Liu et al.

Paper's motivation: Proposes a novel adjustment model for mosaicking low-overlap sweeping images captured by medium-altitude unmanned aerial vehicle (UAV) with a long focal length.

Evaluation: "using the proposed adjustment model versus direct homographic transformation."

RMSE was used as the metric.

TABLE I

POSITIONING ACCURACY COMPARED TO THE DIRECT RECTIFICATION

GPS\IMU Accuracy	RMSE	GPS\IMU Accuracy	RMSE
0.10m\0.02°	0.758m	0.10m\0.02°	0.758m
0.10m\0.10°	2.720m	0.50m\0.02°	0.964m
0.10m\0.20°	5.129m	1.00m\0.02°	1.279m
0.10m\0.40°	12.566m	2.00m\0.02°	1.937m
0.10m\0.80°	23.052m	3.00m\0.02°	2.326m

Thermal Mosaicing Softwares

- Pix4Dmapper
    - Commercial
- PTGui
    - Commercial
    - Ranked 1st by [3] (proposed method notwithstanding)
- Autostitch
    - Software
    - Ranked 3rd (last) by [3]
- Liu's Method
    - Paper
    - Ranked 2nd by [3]
- GSP
    - Paper
    - Github implementation

References

1. Chen, Y.-S., & Chuang, Y.-Y. (2016). Natural image stitching with the global similarity prior. In B. Leibe, J. Matas, N. Sebe, & M. Welling (Eds.), Computer Vision – ECCV 2016 (pp. 186–201). Springer International Publishing. https://doi.org/10.1007/978-3-319-46454-1_12
2. Ieee xplore full-text pdf: (n.d.). Retrieved June 2, 2024, from https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9229104
3. Jin, X., Wang, C., Han, G., Wang, Y., & Jia, J. (2024). A novel stitching method for high-precision low-overlap thermal infrared array sweeping images. IEEE Transactions on Geoscience and Remote Sensing, 62, 1–17. https://doi.org/10.1109/TGRS.2023.3337244
4. Liu, J., Gong, J., Guo, B., & Zhang, W. (2017). A novel adjustment model for mosaicking low-overlap sweeping images. IEEE Transactions on Geoscience and Remote Sensing, 55(7), 4089–4097. https://doi.org/10.1109/TGRS.2017.2688385
5. Zhao, J., Zhang, X., Gao, C., Qiu, X., Tian, Y., Zhu, Y., & Cao, W. (2019). Rapid mosaicking of unmanned aerial vehicle (Uav) images for crop growth monitoring using the sift algorithm. Remote Sensing, 11(10), 1226. https://doi.org/10.3390/rs11101226

To-Do Next

- Check RMSE (https://ieeexplore.ieee.org/document/6619147)
-

Meeting
27/05/2024

Agenda

- Discussion on Ground Truth
  - Reference Image as Ground Truth
  - Evaluation without Ground Truth
- Common Evaluation Metrics
- Mosaicing Algorithms and Softwares

- Categorization of Image Mosaicing Techniques
- Databases (or lack thereof)

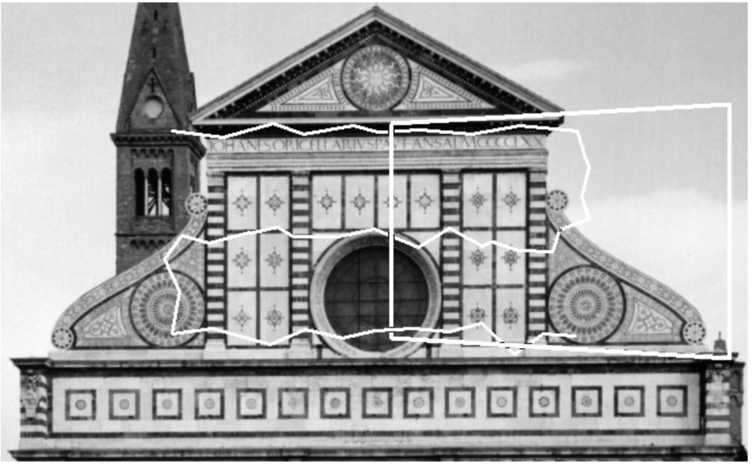
Ground Truth

1. Reference Image as Ground Truth

<u>Paper</u>: Objective evaluation of image mosaics, Boutellier, et al.

<u>Paper's motivation</u>: creating an objective method of measuring quality of stitching results.

GT creation: Pan a simulated camera over the reference image in a zig-zag pattern taking shots at a semi-constant interval. After that a series of image distortions are applied to each individual shot to further simulate a naturally taken mosaic image.



Distortions simulated:

- Perspective warp, Radical distortion, Motion blur, Rotation, Exposure time difference, Lens vignetting

Ground Truth

1. Reference Image as Ground Truth

Example & Distortion method

Distortion	Application Method
Perspective warp	—
Radical (Barrel) distortion	Calculating new distance for each pixel from the center of the image via the function: $$d_n = d + kd^3$$ - d: distance from image center - d_n: new distance from image center - k: distortion strength parameter
Motion blur	Filtering the source image with a point-spread function consisting of a line with random length and direction.
Rotation	—
Exposure time difference	Normalizing the mean of the image to a constant value
Lens vignetting	Multiplying the image with a two dimensional mask causing intensity to dim slightly.

Ground Truth

1. Reference Image as Ground Truth

Evaluation method:

After the mosaic is created, registration occurs between the mosaic and the ground truth image, then the Structural Similarity Index (SSIM) is calculated.

The score is then as reliable as the registration algorithm used.

Algorithm	Pattern	Facade	Graffiti
UBC Autostitch	0.81 (7), blur, slight dc	0.89 (8), blur	0.76, blur
Mobile stitcher	0.80 (7), dcs	0.68, dcs	0.65, dcs
Surveillance stitcher	0.75 (7), blur, dc	0.86, blur, slight dc	0.72 (6), blur, dc

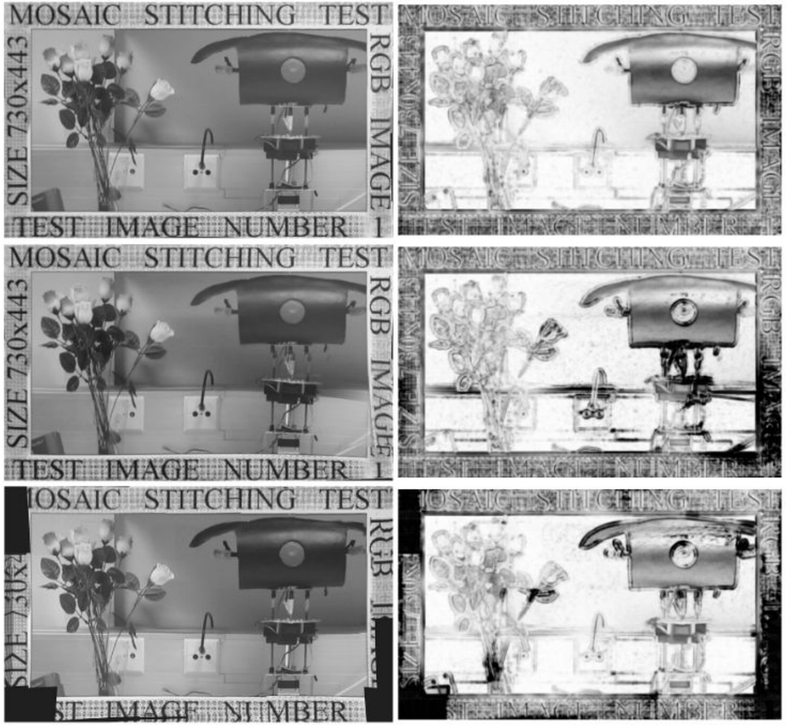


Fig. 8. Mosaics created by three different mosaicking algorithms and the corresponding similarity maps

Ground Truth

1. Reference Image as Ground Truth

<u>Other papers</u>:

- Image based quantitative mosaic evaluation with artificial video, Paalanen et al.
  - Artificial video of mosaicing images is created through a defined scan path of one base image
- Quantitative evaluation of image mosaicing in multiple scene categories, Ghosh et al.
  - Synthetically generated both ground truth and mosaicing frames from one wide-angle reference image

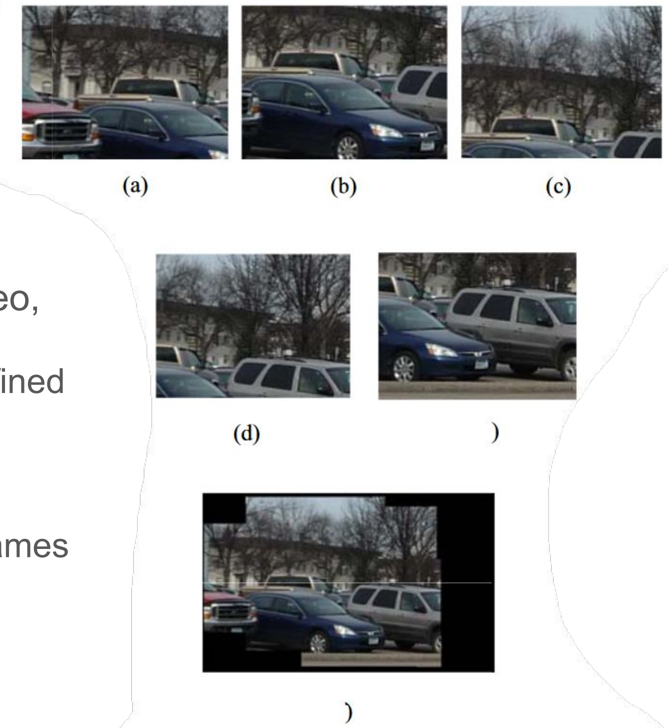
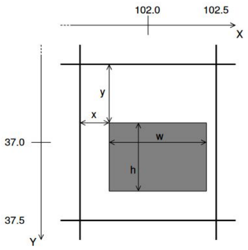
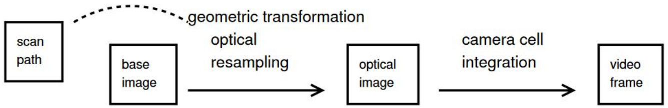


Fig. 3. Example of results corresponding to 3-D data sequence of frames and their corresponding mosaicing output:





Ground Truth

2. Evaluation without Ground Truth

Paper: Performance Evaluation Approach for Image Mosaicing Algorithm, Weibo, et al.

Paper's motivation: constructing a complete evaluation indicators system for image mosaicing algorithms.

Introduces a framework that divides the quality measure of a mosaic image into three categories: accuracy of image registration, blending effect of the overlap, and the visual effect of the overall image. Further explains that the latter category is a measure independent of ground truth.

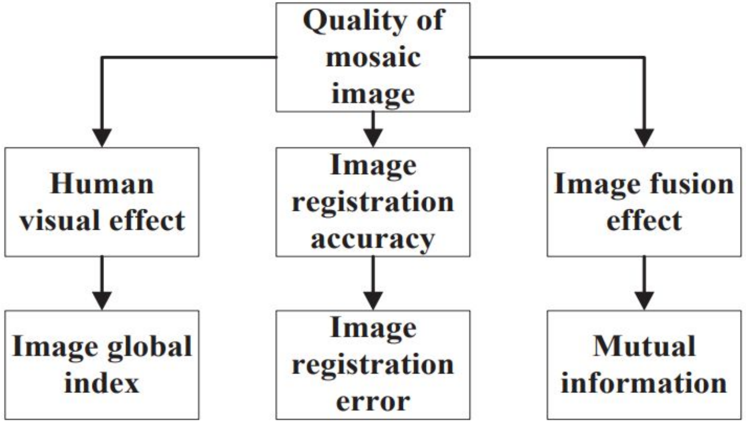


Fig 1. The framework of evaluation indicators system

Ground Truth

2. Evaluation without Ground Truth

Briefly introduces a few measures that can be conducted to determine the quality of an image without referencing ground truth. Namely, the three components of what it calls global image indices:

- Entropy (E)
- Average gradient (G)
- Spatial frequency (SF)

Continues on to list more metrics that can be used in the presence of ground truth, discussed more in the metrics section.

$$E = -\sum_{g=0}^{l-1} p(g) \cdot \log_2 p(g) \qquad (1)$$

$$\overline{G} = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} \sqrt{\frac{\left(\left(\frac{\partial G(i,j)}{\partial i}\right)^2 + \left(\frac{\partial G(i,j)}{\partial j}\right)^2\right)}{2}} \qquad (2)$$

$$RF = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=2}^{N} \left[G(i,j) - G(i,j-1)\right]^2} \qquad (3)$$

$$CF = \sqrt{\frac{1}{M \times N} \sum_{i=2}^{M} \sum_{j=1}^{N} \left[G(i,j) - G(i-1,j)\right]^2} \qquad (4)$$

$$SF = \sqrt{RF^2 + CF^2} \qquad (5)$$

Ground Truth

2. Evaluation without Ground Truth

Paper: Quantitative Evaluation of Panorama Softwares, Sharma, et al.

Paper’s motivation: to identify the best software for panoramic image stitching.

Claim their evaluation falls under full-reference, ie, evaluation where reference images are available. However they do not outright claim to create ground truth neither do they show a reference panorama. Dataset examples they showed can be seen to the right.

Fig. 1 Scene containing buildings (dataset 1)

Fig. 2 Scene containing buildings (dataset 2)

Fig. 3 Indoor scene (dataset 3)

Ground Truth

2. Evaluation without Ground Truth

Evaluation Methodology:

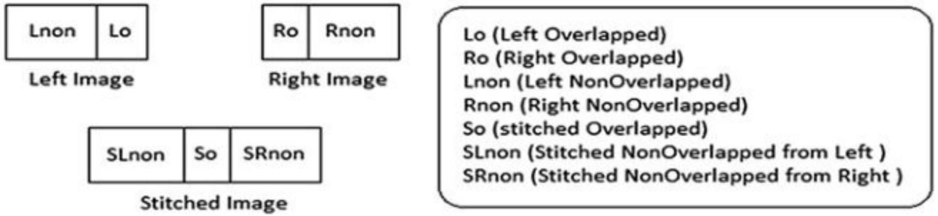


Fig. 5 Comparison of input and stitched images

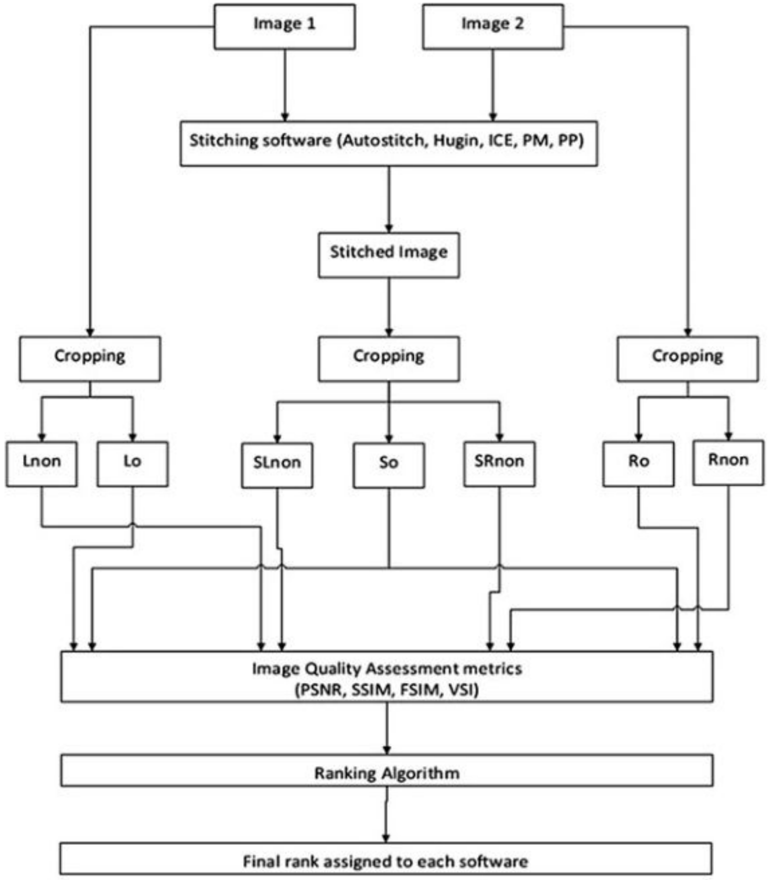


Fig. 6 Workflow adopted for panoramic image quality assessment

Common Evaluation Metrics

Further detail here.

Metric	Overview	Equation	Works
Peak Signal-to-Noise Ratio (PSNR)	The most widely used metric to evaluate picture quality. Measures the ratio between the max power of a signal and the power of corrupting noise.	$PSNR = \frac{10log(max(G(i,j), O(i,j)))^2}{MSE}$	[3] [4] [6]
Structural Similarity Index (SSIM)	Measurement of the quality of a target provided a reference (ground truth) for comparison. It takes into account Weber's law regarding the human visual system and accordingly evaluates the luminescence and contracts scores together with a structural similarity component.	$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$	[1] [4] [5] [6]
Feature Similarity Index (FSIM)	A feature similarity score based on phase congruency (PC) and gradient magnitude (GM).	$FSIM = \frac{\sum_{X \in \Omega} S_L(X) \cdot PC_m(X)}{\sum_{X \in \Omega} PC_m(X)}$	[4]
Visual Saliency Index (VSI)	Takes into account the image's visual saliency, or which areas of the image draw the most attention from the human visual system.	$VSI = \frac{\sum_{X \in \Omega} S(X) \cdot VS_m(X)}{\sum_{X \in \Omega} VS_m(X)}$	[4] [7]
Root Mean Square Error (RMSE)	A classic measure of difference, used to compare the mosaic and its reference image.	$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[Z(i,j) - R(i,j)]^2}{M \times N}}$	[6]

Common Evaluation Metrics

Further detail here.

Metric	Overview	Equation	Works
Correlation Coefficient C	Reflects the degree of correlation between two images.	$C = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left[\left(Z(i,j)-\overline{Z}\right)\left(R(i,j)-\overline{R}\right)\right]}{\sqrt{\left[\sum_{i=1}^{n}\sum_{j=1}^{n}\left(Z(i,j)-\overline{Z}\right)^2 \sum_{i=1}^{n}\sum_{j=1}^{n}\left(R(i,j)-\overline{R}\right)^2\right]}}$	[6]
Mutual Information (MI)	A measurement of the asymmetry between images along with its fluctuation from the mean value.	$MI = \sum_{i=0}^{l-1}\sum_{j=0}^{l-1} p_{ZR}(Z,R)\log_2 \frac{p_{ZR}(Z,R)}{p_Z(i)\,p_R(j)}$	[3] [6]
Percentage of Mismatches	Reflects the number of mismatching pixels between two images beyond a chosen threshold.	—	[3]
Average Difference of Pixel Intensities	A measure of the error in pixel intensities along with their fluctuation from the mean error value.	—	[3]
[GT-independent] Entropy (E)	Measures the richness of information in the image via value probabilities.	$E = -\sum_{g=0}^{n} p(i) \cdot log_2\, p(i)$	[6]
[GT-independent] Average Gradient ($\overline{G}$)	Reflects the amount of detail that the image has, ie, its clarity, via its contrast.	$\overline{G} = \frac{1}{(M-1)(N-1)}\sum_{i=1}^{M-1}\sum_{j=1}^{N-1}\sqrt{\frac{\left(\left(\frac{\partial G(i,j)}{\partial i}\right)^2+\left(\frac{\partial G(i,j)}{\partial j}\right)^2\right)}{2}}$	[6]
[GT-independent] Spatial Frequency (SF)	Reflects the level of activity, i.e. busy-ness of the image, in an image space.	$RF = \sqrt{\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=2}^{N}\left[G(i,j)-G(i,j-1)\right]^2}$ $CF = \sqrt{\frac{1}{M\times N}\sum_{i=2}^{M}\sum_{j=1}^{N}\left[G(i,j)-G(i-1,j)\right]^2}$ $SF = \sqrt{RF^2+CF^2}$	[6]

Mentioned Mosaicing Algorithms/Softwares

Paper: Quantitative Evaluation of Panorama Softwares, Sharma, et al.

- Autostitch
  - original paper
  - more recent paper
  - software
- Panorama Plus
  - page likely changed
- Panorama Maker
  - page not found
- Image Composite Editor
  - software
- Hugin
  - software

Sl. no.	Method name	Rank
1.	Autostitch	1
2.	PP	2
3.	PM	3
4.	ICE	4
5.	Hugin	5

Table 10 Ranking of software products for all three datasets combined

Mentioned Mosaicing Algorithms/Softwares

Paper: Quantitative Evaluation of Panorama Softwares, Sharma, et al.

- Autostitch
  - original paper
  - more recent paper
  - software
- Surveillance Stitcher
  - original paper
- Mobile Stitcher
  - original paper

Table 2. Mosaic quality values and visually observed distortions of test mosaics. The numbers in braces indicate which figure displays the corresponding result, if it is shown. DC is an abbreviation discontinuity.

Algorithm	Pattern	Facade	Graffiti
UBC Autostitch	0.81 (7), blur, slight dc	0.89 (8), blur	0.76, blur
Mobile stitcher	0.80 (7), dcs	0.68, dcs	0.65, dcs
Surveillance stitcher	0.75 (7), blur, dc	0.86, blur, slight dc	0.72 (6), blur, dc

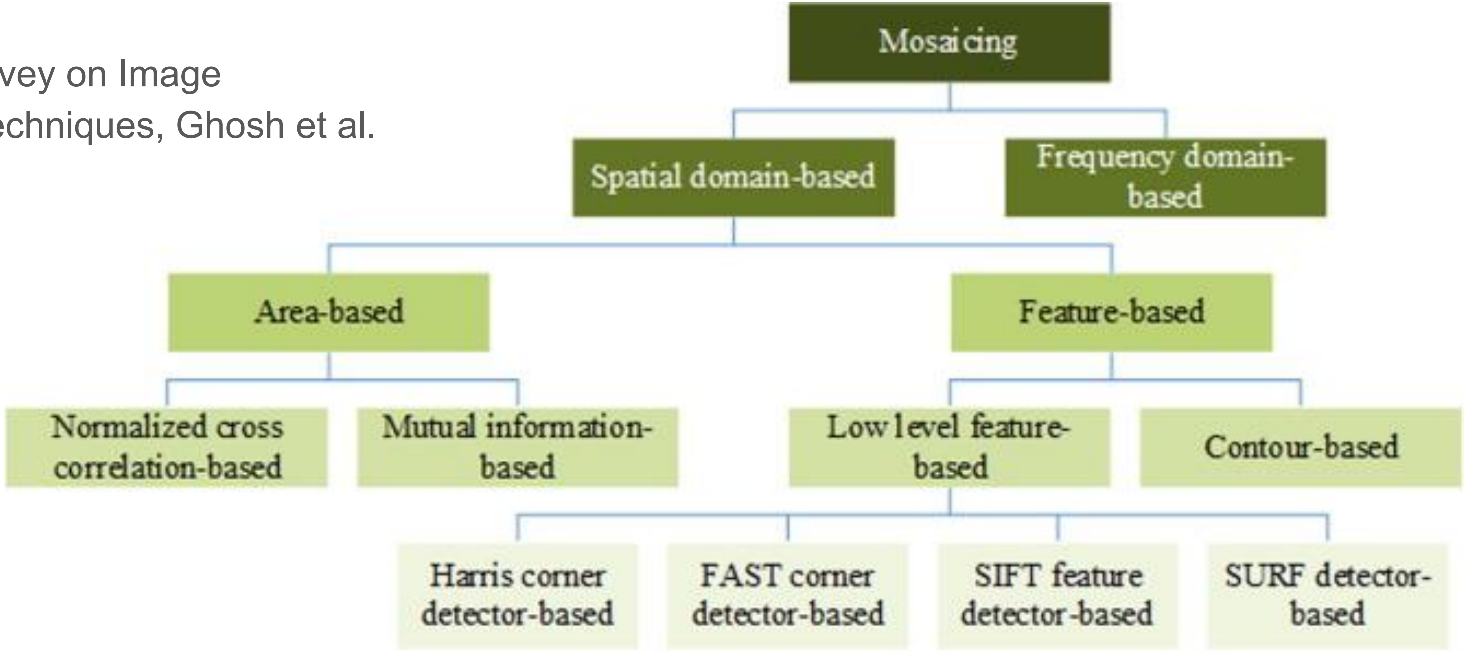
References

1. Boutellier, J., Silvén, O., Tico, M., & Korhonen, L. (2008). Objective evaluation of image mosaics. In J. Braz, A. Ranchordas, H. J. Araújo, & J. M. Pereira (Eds.), *Computer Vision and Computer Graphics. Theory and Applications* (Vol. 21, pp. 107–117). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-89682-1_8
2. Paalanen, P., Kämäräinen, J.-K., & Kälviäinen, H. (2009). Image based quantitative mosaic evaluation with artificial video. In A.-B. Salberg, J. Y. Hardeberg, & R. Jenssen (Eds.), *Image Analysis* (Vol. 5575, pp. 470–479). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-02230-2_48
3. *Quantitative evaluation of image mosaicing in multiple scene categories | IEEE Conference Publication | IEEE Xplore*. (n.d.). Retrieved May 25, 2024, from https://ieeexplore.ieee.org/abstract/document/6220726
4. Sharma, S. K., Jain, K., & Suresh, M. (2019). Quantitative evaluation of panorama softwares. In A. Kumar & S. Mozar (Eds.), *ICCCE 2018* (Vol. 500, pp. 543–561). Springer Singapore. https://doi.org/10.1007/978-981-13-0212-1_56
5. Wang, Z., Bovik, A. C., Sheikh, H. R., & Simoncelli, E. P. (2004). Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing*, *13*(4), 600–612. https://doi.org/10.1109/TIP.2003.819861
6. Weibo, Z., Jianxun, L., & Zhi, Z. (2013). Performance evaluation approach for image mosaicing algorithm. *2013 25th Chinese Control and Decision Conference (CCDC)*, 3786–3791. https://doi.org/10.1109/CCDC.2013.6561608
7. Zhang, L., Shen, Y., & Li, H. (2014). Vsi: A visual saliency-induced index for perceptual image quality assessment. *IEEE Transactions on Image Processing*, *23*(10), 4270–4281. https://doi.org/10.1109/TIP.2014.2346028

Categorization of Image Mosaicing Techniques

Registration Based

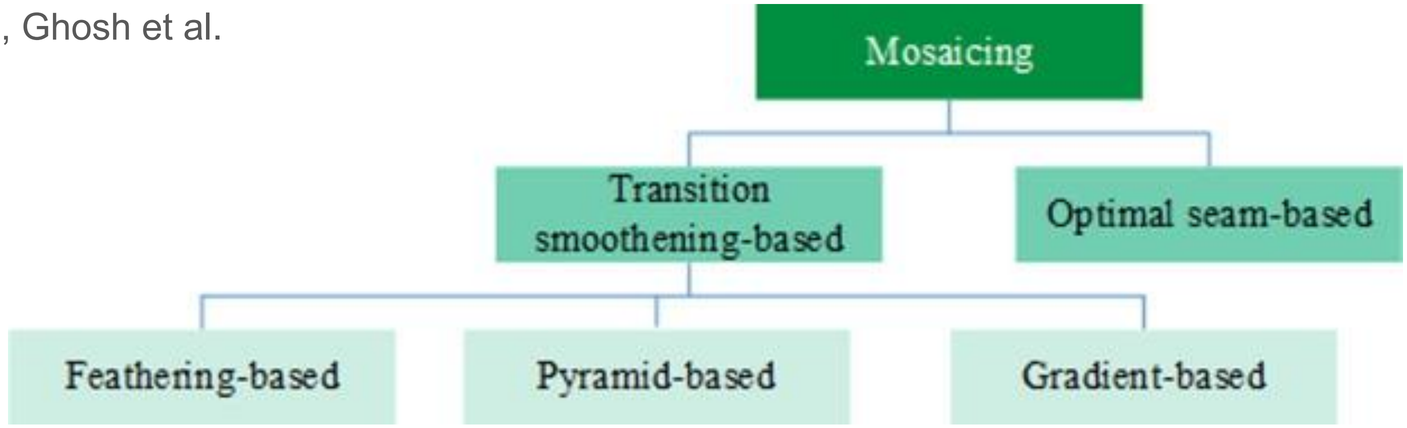
Paper: A Survey on Image Mosaicing Techniques, Ghosh et al.



Categorization of Image Mosaicing Techniques

Blending Based

Paper: A Survey on Image Mosaicing Techniques, Ghosh et al.



Categorization of Image Mosaicing Techniques

Table 1
Comparative overview of different categories of mosaicing methods based on image registration.

Category	Advantages	Disadvantages
NCC-based	No high level structural analysis required, and can be applied directly to image data	Flat similarity due to self-similarity of images, and good only for images with large overlapping
MI-based	Good for multimodal analysis and less sensitive to illumination and occlusion changes	Slow and causes registration error when images have small overlapping
Harris corner detector-based	Simple and accurate computation	Needs prior knowledge of window size and good only for moderate changes in scale and rotation
FAST corner detector-based	Accurate and fast computation	Not robust to high degree of noise, and prior knowledge about threshold required
SIFT feature detector-based	Efficient for high resolution images and offers invariance to various transformations	Computationally expensive
SURF detector-based	Fast computation, good for real-time applications	Poor performance under certain transformations (e.g. color, illumination)
Contour-based	Efficient when large and complicated motion involved	Computationally expensive because of the use of high-level features
Frequency domain-based	Efficient because of FFT	Overly sensitive to noise and accuracy relies on large overlapping

Databases?

UMCD Dataset

Paper: A UAV Video Dataset for Mosaicing and Change Detection From Low-Altitude Flights, Avola et al.

“The first collection of geo-referenced video sequences acquired at low-altitude for mosaicking and change detection purposes.”

Download Available here, password requested via email at avola@di.uniroma1.it

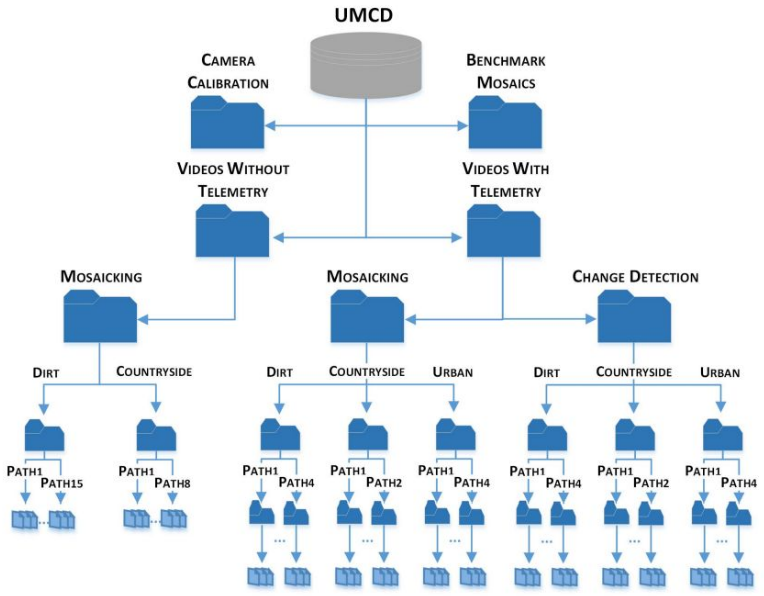


Fig. 1. Main structure of the UMCD dataset.

To-Do Next

- Focusing on Thermal Mosaicing
  - Software packages (commercial)
- Mimicking / synthetic thermal ground truth gen
- Learning more about thermal imaging
  - Formats: FLIR, 14-bit TIFF
  - IR (blend RGB + Thermal) vs raw thermal
- Check notebook
- Milestone (next two weeks):
  - Run existing image stitching techniques (software available) with the thermal dataset we create

Meeting
20/05/2024

Agenda

- Status report
  - What metrics? Dataset / ground truth?
  - Section metrics
    - Table, brief discussion of each metric
  - Section datasets and ground truth
    - Artificial images, etc
  - Check for datasets available
- Algorithms?
- Check book
  - https://link.springer.com/book/10.1007/978-3-030-34372-9

[...]

[...]

Kickoff Meeting 12/05/2024

Agenda

- Aligning expectations: Advisor-Student Agreement (30 min)
- Onboarding (20 min)
    - Google Drive
    - Zotero
    - Guidelines
- Scheduling weekly meetings (5 min)
- Revise proposal (next week)
- Next steps (15 min)
    - Check How to Read a Paper resources
    - Read this paper:
        - Understand the main ideas, answer questions like:
            - What are the contributions of this paper?
            - What is the methodology?
            - What are the assumptions?
        - https://drive.google.com/file/d/1FFvlb_Y_Nac5qM5ypKXNuq2BN1vKz0VS/view?usp=drive_link
    - Literature review
        - Thermal PV Inspection using robotic tools
        - Mosaicking
            - What metrics/experiments do they do?