Exploring the Effects of Color Maps on Stitching Close-Range Thermal Images of Solar Panels

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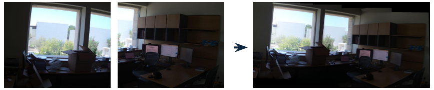
Abstract

Image mosaicing is widely used across various fields, but challenges remain in thermal imaging, especially for close-range images. We investigate how color maps impact the stitching quality of close-range thermal images by testing 11 color maps and 3 range selection strategies. The results are quantitatively evaluated to identify the best colormap options.

Our findings show that focusing the colormap range on the most frequent values significantly improves mosaic quality. Among the color maps tested, Magma and Inferno consistently performed well across all metrics. Our findings highlight the importance of color map selection in thermal image mosaicing

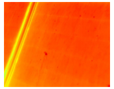
Background

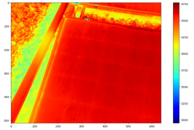
Image stitching is a process in which individual images are combined into one wide-angle mosaic. For example:



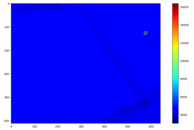
Thermal image mosaicing is notably more arduous. Temperature magnitudes are visualized through color, and the reconstructed thermal images suffer from fewer visible features than RGB images.

In this work, we attempt to increase the stitching quality of close-range thermal solar panel images by optimizing the color map used to represent them.





vs.

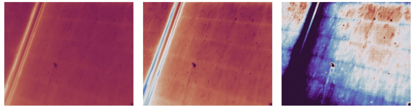


Methodology

The dataset used in this paper consists of fourteen different sequences of radiometric images, altogether making up 56 possible mosaic pairs. All 56 image pairs were inputted into a traditional SIFT-based stitching pipeline (where SIFT is a feature detection computer vision algorithm), then into another pipeline for quantitative evaluation of the results.

Three color map ranges and eleven color maps were tested using the dataset. The ranges were as follows:

- **Full Range:** Uses the lowest and highest thermal values in the image sequence as colormap limits, capturing all data but reducing visual distinction.
- **Averaged Range:** Sets limits based on the average max and min thermal values in the image sequence, slightly improving visual clarity but still being potentially impacted by sun flares.
- **Focused Range:** Focuses the range on the 70 most frequent values, enhancing subtle thermal differences like busbar visibility on solar panels.



(a) Full Range (b) Averaged Range (c) Focused Range

Fig. 1: Examples of the three ranges applied to the same image.

The eleven colormaps tested are: Hot, Inferno, Magma, Plasma, Viridis, Cividis, HSV, Twilight Shifted, Twilight, CMRmap, and Jet.

Results & Conclusions

Results:

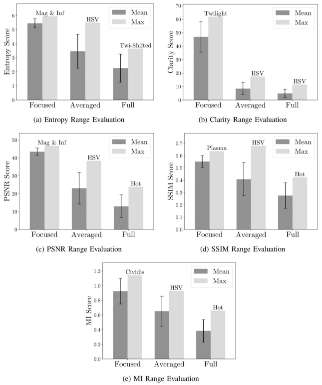
- The **focused range** of color maps generally **outperformed the full and averaged ranges** across all metrics as shown in Fig. 3.
- Color maps **Magma** and **Inferno** consistently ranked high (top 5) across all metrics due to their uniform lightness levels.
- **Stitching failures** were more frequent with full and averaged ranges due to fewer detected features as shown in the table below.

TABLE I: Failure Percentages for Different Color Maps

Color Map	Failure %	Color Map	Failure %
Hot focused	0.0%	Magma focused	1.8%
Hot averaged	57.1%	Magma averaged	51.8%
Hot full	58.9%	Magma full	78.6%
Inferno focused	1.8%	Plasma focused	5.4%
Inferno averaged	51.8%	Plasma averaged	67.9%
Inferno full	42.9%	Plasma full	80.4%
Jet focused	0.0%	Viridis focused	14.3%
Jet averaged	35.7%	Viridis averaged	78.6%
Jet full	67.9%	Viridis full	91.1%
Cividis focused	5.4%	Twilight focused	0.0%
Cividis averaged	75.0%	Twilight averaged	33.9%
Cividis full	85.7%	Twilight full	66.1%
HSV focused	0.0%	CMRmap focused	3.6%
HSV averaged	16.1%	CMRmap averaged	57.1%
HSV full	53.6%	CMRmap full	78.6%
Twi-Shifted focused	0.0%		
Twi-Shifted averaged	32.1%		
Twi-Shifted full	58.9%		

Conclusions:

- **Focusing the colormap** range improves image mosaicing by enhancing subtle thermal differences, especially for solar panels.
- **Sequential color maps** (Magma, Inferno, Plasma, Viridis, Cividis, etc.) performed best, likely due to their uniformly-changing lightness.
- Future research should explore this approach in **other thermal imaging contexts**, with more robust stitching pipelines, and create **specialized metrics for thermal imaging** quality.



(a) Entropy Range Evaluation (b) Clarity Range Evaluation (c) PSNR Range Evaluation (d) SSIM Range Evaluation (e) MI Range Evaluation

Fig. 3: Evaluation results across all color maps.

Evaluation

Our evaluation framework is comprised of two categories of metrics. The first category measures the quality of the mosaic based on texture, blurriness, and the richness of information:

- **Entropy**: Measures information quantity.

$$\text{Entropy} = -\sum_{i=1}^{n} p(x_i)\log_2 p(x_i)$$

- **Clarity**: Assesses sharpness and definition.

$$\text{Clarity} = \sum_{i=1}^{M}\sum_{j=1}^{N} G_{i,j} \qquad G = \sqrt{\frac{\partial I}{\partial x}^2 + \frac{\partial I}{\partial y}^2}$$

The second category involves measuring the similarity between the mosaic and a ground truth image:

- **PSNR**: Evaluates reconstruction accuracy.

$$\text{PSNR} = 20 \cdot \log_{10}\left(\frac{255}{\sqrt{\text{MSE}}}\right)$$

- **SSIM**: Assesses structural similarity.

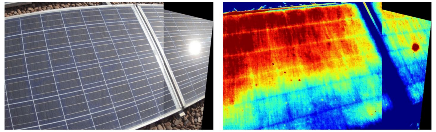
$$\text{SSIM}(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma}$$

- **Mutual Info**: Measures shared information between two images.

$$MI(X;Y) = \sum_{y\in Y}\sum_{x\in X} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right)$$

Due to its nature, there is no “ground truth” for image stitching. We instead compute the “”correct”” stitching homography from the RGB versions of the images. Then we fake-stitch the thermal versions and use those as a reference for evaluation as shown in Fig. 2.

Radiometric images contain both **thermal** and **RGB** data in a single file, which allows us to construct the reference mosaics used for ground truth as described above.



(a) RGB Mosaic (b) Adapted Thermal Mosaic

Fig. 2: Example of thermal ground truth adaption from RGB mosaics