

IMAGE FUSION THROUGH LINEAR EMBEDDINGS

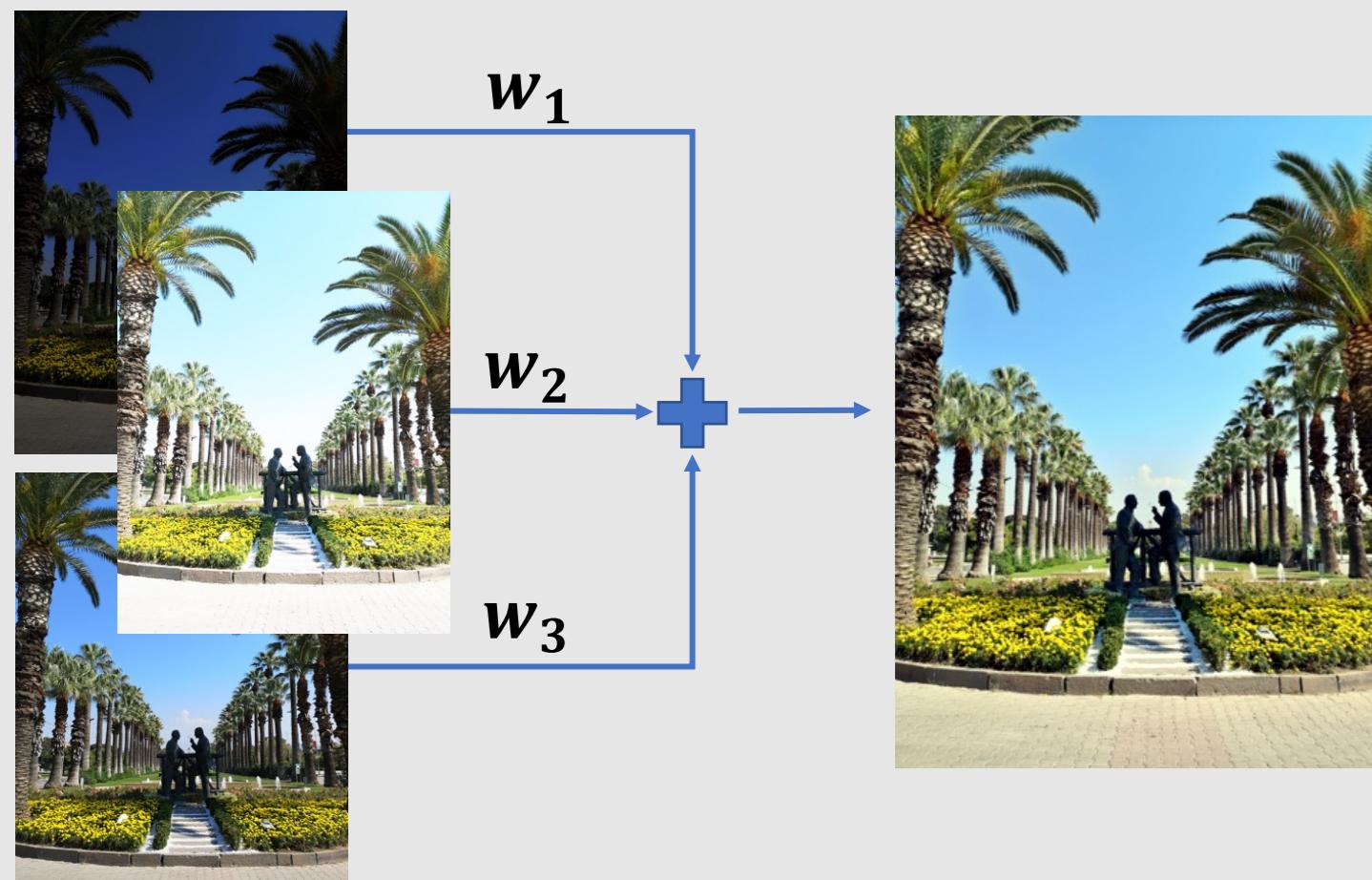
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Problem-Context Definition

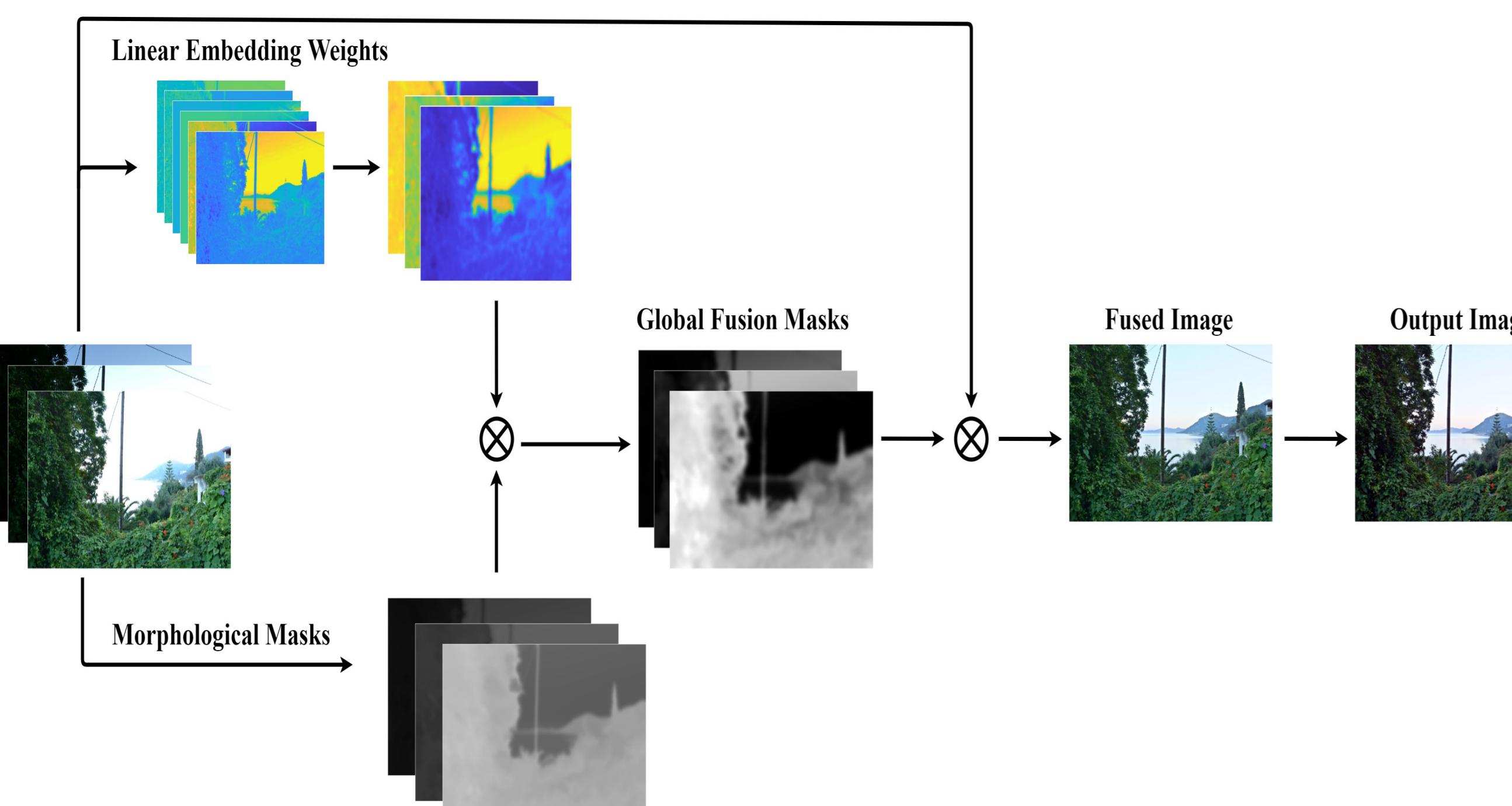
- Fuse images to create more informative content
- Severely over-exposed images result in faulty weight maps
- New framework for weight map characterization
- A method for MEF and its extension to visible-infrared image fusion

Proposed Multi-Exposure Image Fusion Algorithm

- Creating HDR-like content from stack of LDR images



- Preserving
 - Fine details
 - Vivid colors
- By taking advantage of
 - Image Fusion
 - Linear Embeddings
 - Morphological Masking

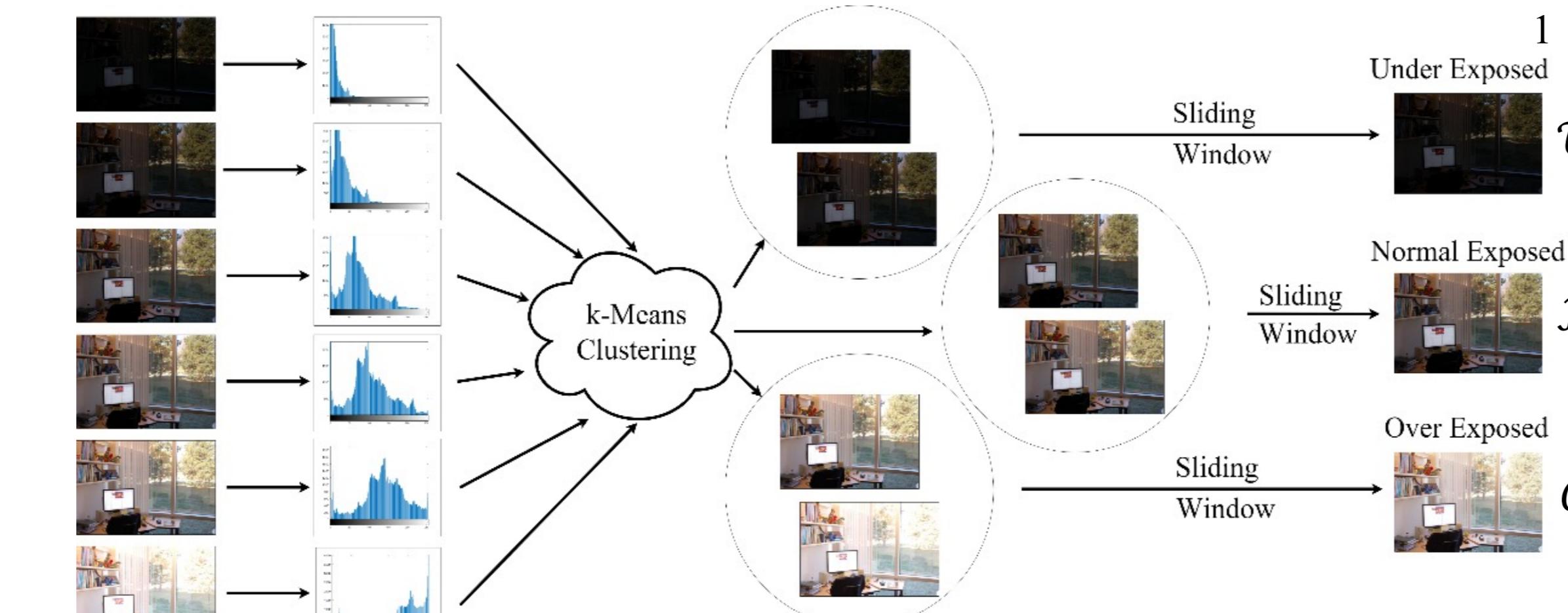


Contributions

A novel and effective image fusion framework:

- Weight map characterization via linear embeddings (LE)
- Map refinement via adaptive morphological operation
- First study benefiting from LE for weight extraction in image fusion

Determination of exposures



- Obtain PDFs to form feature vectors
- Apply k-means clustering method to group all exposures ($k = 3$)
- Apply sliding window technique to each set to obtain 3 exposures

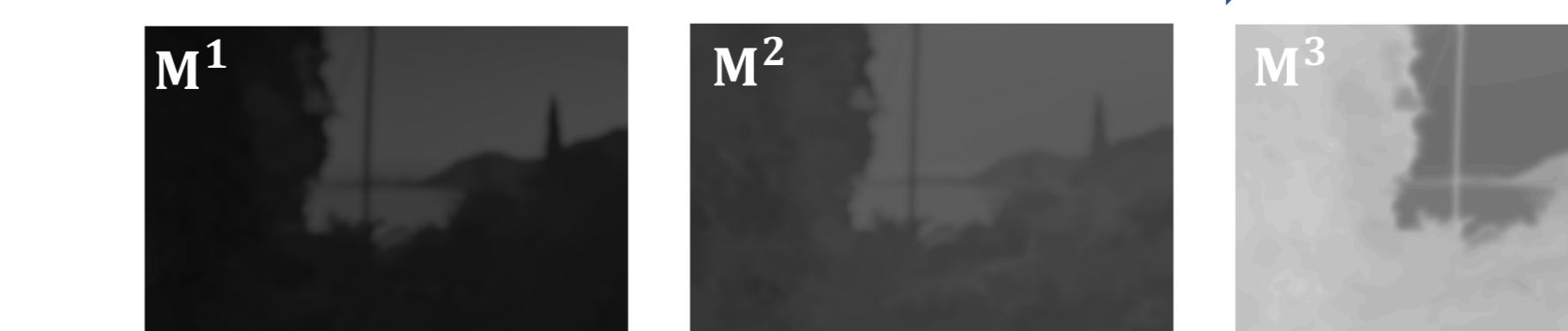
Adaptive morphological masking

- Natural texture
- Remove small blemishes without damaging overall structures



of darkest pixel intensity $U < \#$ of brightest pixel intensity O , $r^* = 20$
 # of darkest pixel intensity $U > \#$ of brightest pixel intensity O , $r^* = 11$

- Opening-by-reconstruction operation



Closing-by-reconstruction

Fusion

Global Fusion Masks

$$\mathbf{G}_1 = \mathbf{M}_1 \otimes \mathbf{E}_3 \quad \mathbf{G}_2 = \mathbf{M}_2 \otimes \mathbf{E}_2 \quad \mathbf{G}_3 = \mathbf{M}_3 \otimes \mathbf{E}_1$$

✓ Top 1% & Bottom 1% pixel values of \mathbf{G}_2 stretch to obtain a more balanced \mathcal{N}

$$\mathbf{F} = \mathbf{U} \otimes \mathbf{G}_1 + \mathbf{N} \otimes \mathbf{G}_2 + \mathbf{O} \otimes \mathbf{G}_3$$

$$\checkmark \text{ Top 1% & Bottom 1% pixel values of } \mathbf{G}_2 \text{ saturated to obtain a more balanced } \mathcal{N}$$



Results for Multi-Exposure Image Fusion



Main Idea

- Preserve
 - Intrinsic geometric characteristics of the manifold
- Sparsity constraint
 - Only neighbors of the patch are of interest
- Sum-to-one constraint
 - Enforces invariance to rotations, rescalings, translations

Weight maps via linear embeddings

$$\begin{aligned} \{\mathbf{W}_i^1, \mathbf{W}_i^2\} &= \arg \min_{\{\mathbf{w}_1, \mathbf{w}_2\}} \left\| \mathbf{o}_i - [\mathbf{u}_i \ \mathbf{n}_i] \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \end{bmatrix} \right\|_2^2 \quad s.t. \quad w_1 + w_2 = 1 \\ \{\mathbf{W}_i^3, \mathbf{W}_i^4\} &= \arg \min_{\{\mathbf{w}_3, \mathbf{w}_4\}} \left\| \mathbf{u}_i - [\mathbf{n}_i \ \mathbf{o}_i] \begin{bmatrix} \mathbf{w}_3 \\ \mathbf{w}_4 \end{bmatrix} \right\|_2^2 \quad s.t. \quad w_3 + w_4 = 1 \\ \{\mathbf{W}_i^5, \mathbf{W}_i^6\} &= \arg \min_{\{\mathbf{w}_5, \mathbf{w}_6\}} \left\| \mathbf{n}_i - [\mathbf{u}_i \ \mathbf{o}_i] \begin{bmatrix} \mathbf{w}_5 \\ \mathbf{w}_6 \end{bmatrix} \right\|_2^2 \quad s.t. \quad w_5 + w_6 = 1 \end{aligned}$$

$\mathbf{o}_i, \mathbf{n}_i, \mathbf{u}_i$ are kernel of Over, Normal, Under Exposed images, respectively
 $\mathbf{W}_{1,2}^j$ are optimal weights

Inspired from LLE²

To obtain LE weights

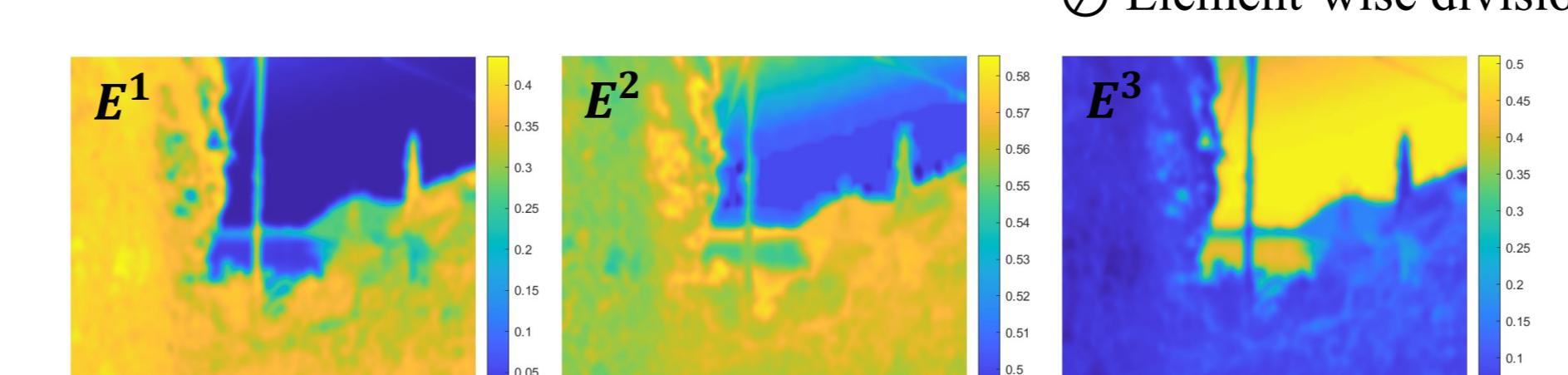
$$\mathbf{E}'_1 = (|\mathbf{W}_1| + |\mathbf{W}_5|) * \mathbf{G}, \mathbf{E}'_2 = (|\mathbf{W}_2| + |\mathbf{W}_3|) * \mathbf{G}, \mathbf{E}'_3 = (|\mathbf{W}_4| + |\mathbf{W}_6|) * \mathbf{G}$$

$$\mathbf{E}_k = \mathbf{E}'_k \oslash (\mathbf{E}'_1 + \mathbf{E}'_2 + \mathbf{E}'_3), k = 1, 2, 3$$

\mathbf{G} Gaussian Filter

* Convolution operation

\oslash Element-wise division



Application for Visible-Infrared Image Fusion*



* Not optimized yet

1) O.Ulucan , D.Karakaya and M.Turkan. (2021) Multi-exposure image fusion based on linear embeddings and watershed masking. *Signal Processing* , Vol. 178, No. 107791

2) Roweis, S. T. and Saul, L. K. (2000) Nonlinear dimensionality reduction by locally linear embedding, *Science*, Vol. 290(5500), pp. 2323–2326.