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## Abstract

Fluorescence microscopy drives progress in the life sciences, but affordable modalities such as widefield microscopy suffer from haze caused by out-of-focus light, unlike high-end confocal microscopes. Computational dehazing aims to combine the accessibility of widefield microscopy with the image quality of confocal imaging. However, the perception-distortion trade-off means methods typically optimize either fidelity (e.g., PSNR, MSE) or realism (e.g., LPIPS, FID), but rarely both. We propose **HazeMatching**, a novel iterative dehazing method based on conditional flow matching that guides the generative process using the hazy observation within the conditional velocity field. HazeMatching balances quantitative fidelity and perceptual realism without requiring an explicit degradation operator, making it applicable to real microscopy data. We evaluate our method on **5 synthetic and real microscopy datasets against 12 baselines**, showing a consistent trade-off between **fidelity and realism** while also producing **well-calibrated predictions** through calibration analysis.

## Background of the Problem

**Image Dehazing (Inverse Problem)**

Degraded → Clean

**No Unique Solution (ill-posed)!**

**Regression-to-Mean Effect (Blurry Structures)[1]**

Typical approach makes the prediction smooth

**(Typical) one-shot restoration approaches**

Input  $y$  → MMSE Estimator  $f()$  → Prediction  $f(y) = \mathbb{E}[x|y]$  → GT  $x$

$\|f(y) - x\|^2$

**Many plausible solutions**

## Why does this happen, and how to fix it?

**Perception-Distortion Tradeoff**

Method that is best on one axis cannot be the best on the other at the same time! [2]

This work: Can we get a Good PDT?

Impossible

**Restricting Averaging**

Restricting the plausible sample averaging space results in a less blurry averaged image.

## Iterative Prediction reduces averaging effect

Haziest → Less Hazy → Very Less Hazy

Iteratively predicting from less degraded images can be thought of as a step-wise reduction in uncertainty thereby restricting averaging!

## Guided Conditional Flow Matching

**Training Data Generation**

Training input data is a linear interpolation of noise and clean data

$X_0 + X_{M_1} = X_t$

$p_t(x|x_{M_1}) = \mathcal{N}(tx_{M_1}, (1-t)^2I)$

The conditional probability path

## Guided Training Scheme

Condition on Degraded Observations  $X_{M_0}$

Flow Model

$\frac{dx_t}{dt} = x_{M_1} - x_0$

Velocity

$\min_{\theta} \mathbb{E} \|v_{\theta}(t, x_t, x_{M_0}) - (x_{M_1} - x_0)\|^2$

## Guided Iterative Inference Scheme

Initial input  $X_0$

$X_{+\delta t}$

$X_{M_1}$

ODE Integration (Euler)

$x_t + T^{-1} \frac{dx_t}{dt}$

Flow Model

Velocity

$v(x_t) = \int v(t, x_t | x_{M_1}) p_{M_1}(x_{M_1} | x_t) dx_{M_1}$

The marginal velocity field

## Conclusions

- We introduce **HazeMatching**, an ODE-based iterative method for computational dehazing that restricts the averaging space to navigate the perception-distortion tradeoff.
- Flow Matching models are particularly effective in settings with high uncertainty, such as severe haze and strong signal degradation.
- This improved visual fidelity comes with the inherent challenge of higher computational costs compared to standard one-shot inference methods. Future work will optimize for throughput.

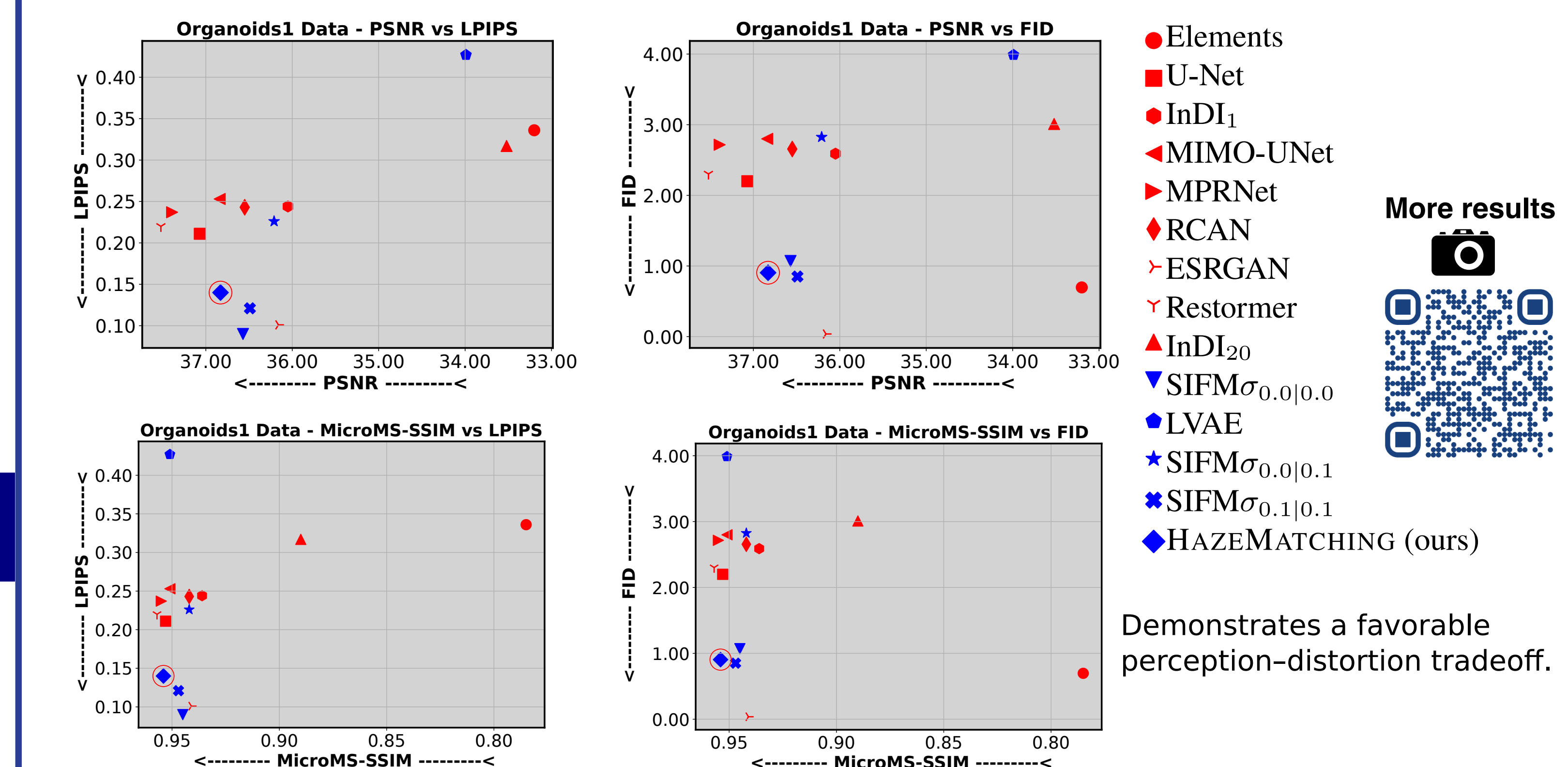
## Qualitative Results (Organoids1 Data)

(a) Input Frame (1024 x 1024) (b) Cropped Frame (128 x 128) (c) Cropped GT (d) Elements (PSNR: 24.18, LPIPS: 0.63) (e) UNet (PSNR: 25.97, LPIPS: 0.37)

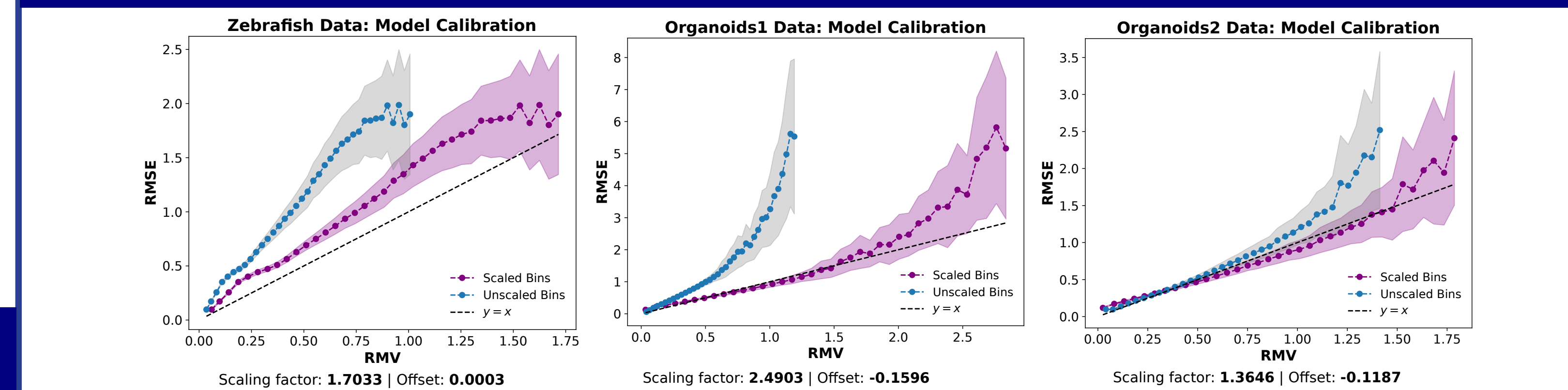
(f) RCAN (PSNR: 25.34, LPIPS: 0.46) (g) ESRGAN (PSNR: 25.11, LPIPS: 0.13) (h) InDI<sub>20</sub> (PSNR: 25.89, LPIPS: 0.13) (i) SIFM  $\sigma_{0.1|0.1}$  (PSNR: 26.46, LPIPS: 0.13) (j) HazeMatching (ours) (PSNR: 26.74, LPIPS: 0.21)

Yellow arrow indicates regions where UNet and SIFM produces oversmooth structures while HazeMatching prediction is closer to the Ground Truth.

## Quantitative Results (Organoids1 Data)



## Model Calibration Performance



Calibration plots across 3 datasets shown here demonstrate that the model's posterior variance is strongly correlated with the model's prediction error.

## References

- [1] Delbracio, M. and Milanfar, P. (2023). Inversion by direct iteration: An alternative to denoising diffusion for image restoration. TMLR 2023.
- [2] Blau, Y. and Michaeli, T. (2018). The perception-distortion tradeoff (CVPR 2018)