Contextual Hypernetwork for Adaptive Prediction of Laser-Induced Colors on Quasi Random Plasmonic Metasurfaces

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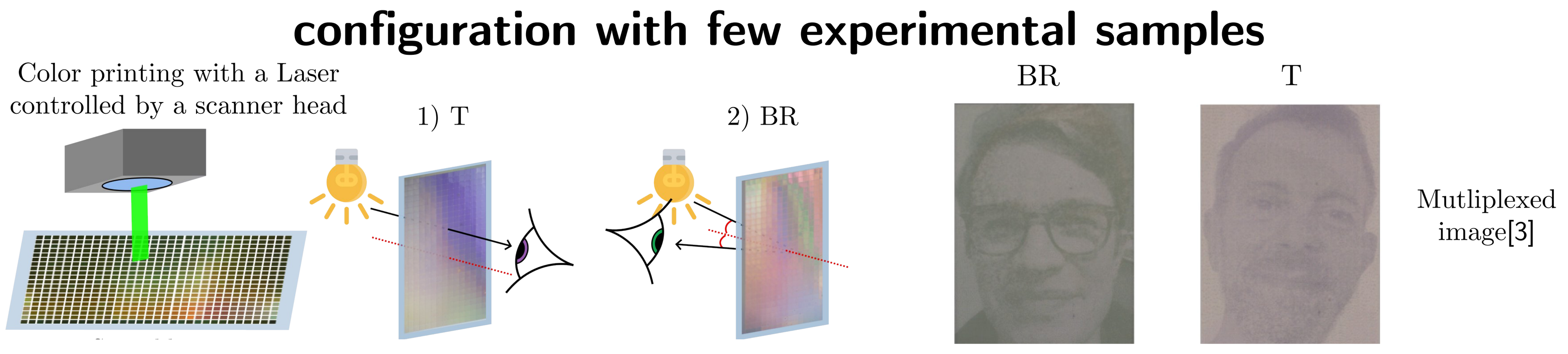
Introduction

Context: Plasmonic Metasurfaces are thin film made of metallic or dielectric periodic structures[1] that can be produced by laser processing thin film embedding silver nanoparticles[2]. The resulting colors are used for anticounterfeiting[3] applications through color image multiplexing

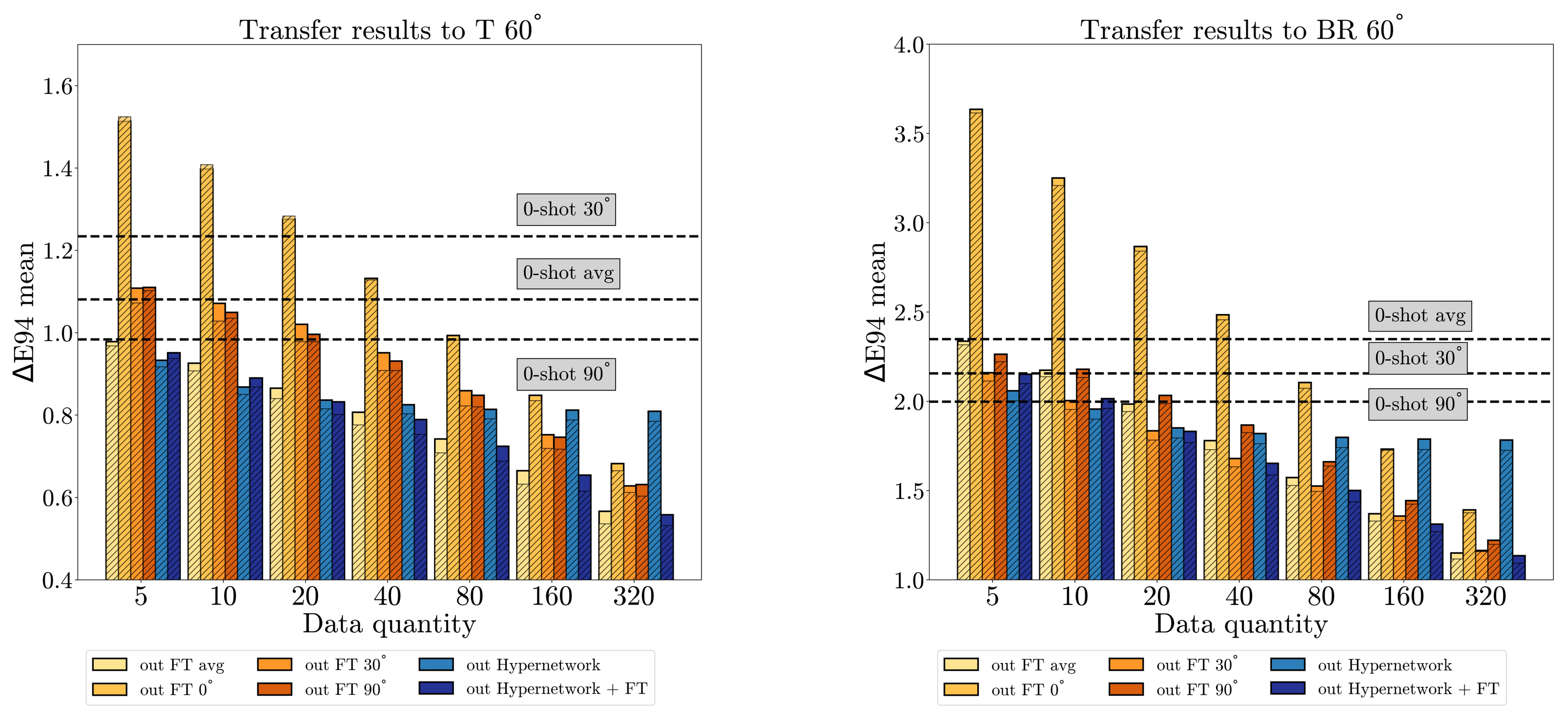
Objective: Learning a model from experimental data that adapts to different experimental conditions to predict the resulting colors induced by laser processing.

Dataset: 9600 experimental samples are acquired in two observation modes, Transmission (T) and Backside Reflection (BR), associating Laser Power, Scan Speed, Repetition Rate, Interline Distance and Laser Polarization Angles to CIE Lab colors[4]

$\Longrightarrow$ **Model Based Hypernetwork to adapt to new processing configuration with few experimental samples**



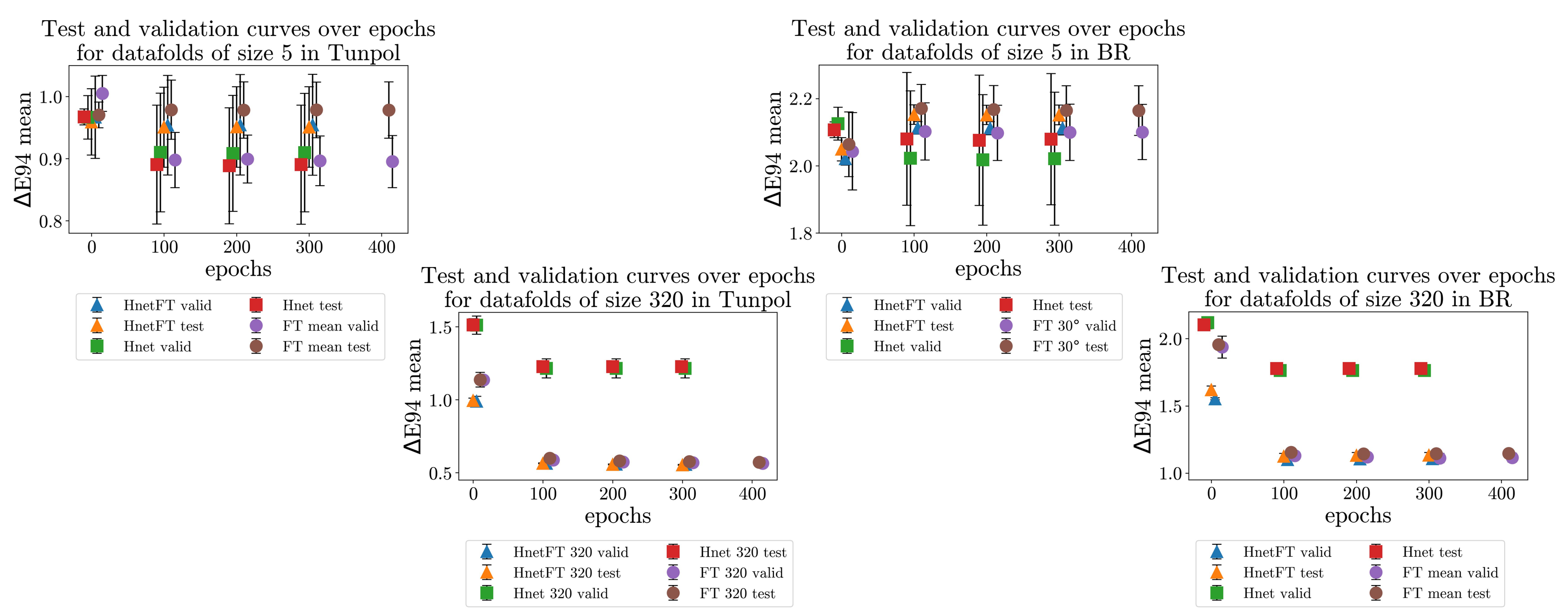
Quantitative Results



Exp Name	To T 60° Δ E94 mean	To T 60° Δ E94 std	To T 60° Accuracy (%)	To BR 60° Δ E94 mean	To BR 60° Δ E94 std	To BR 60° Accuracy (%)
0-shot	0.98± 0.04	0.79± 0.013	84.69± 1.33	2.00± 0.09	1.18± 0.04	38.12± 5.72
Target-320	0.92± 0.07	0.85± 0.12	71.09± 3.78	1.60± 0.18	1.30± 0.12	60.21± 2.47
FT-320	0.57± 0.05	0.47± 0.08	95.21± 2.12	1.15± 0.04	0.84± 0.08	75.87± 2.93
Hnet-320	0.80± 0.02	0.57± 0.03	89.34± 0.55	1.78± 0.02	1.06± 0.05	47.01± 1.47
HnetFT-320	**0.56± 0.03**	**0.45± 0.07**	**95.76± 1.33**	**1.13± 0.04**	**0.84± 0.10**	**76.32± 2.78**
WANN-320	1.05± 0.03	0.85± 0.10	82.93± 1.33	2.02± 0.03	1.32± 0.08	38.75± 1.78
Target-40	2.08± 0.27	1.64± 0.32	46.46± 5.97	5.88± 0.65	3.73± 0.44	5.65± 2.71
FT-40	0.81± 0.05	0.47± 0.08	89.69± 2.42	1.78± 0.09	1.08± 0.09	48.08± 4.53
Hnet-40	1.24± 0.04	0.76± 0.09	73.39± 2.27	1.82± 0.06	1.07± 0.05	45.35± 3.02
HnetFT-40	**0.79± 0.05**	**0.58± 0.07**	**90.48± 2.32**	**1.65± 0.09**	**1.01± 0.09**	**52.71± 4.40**
WANN-40	1.05± 0.03	0.85± 0.10	82.93± 1.50	2.03± 0.03	1.32± 0.09	37.92± 2.54

Target-X: Learned from scatch using X samples, FT-X: Finetuned from the mean angles response, Hnet-X: Adapted with Hypernetwork, HnetFT-X: Adapted with hypernetwork then finetuned, WANN[6]-X: Source reweighting to handle covariance shift
X: Used number of samples

→ Reduced variance is observed with Hypernetwork learning

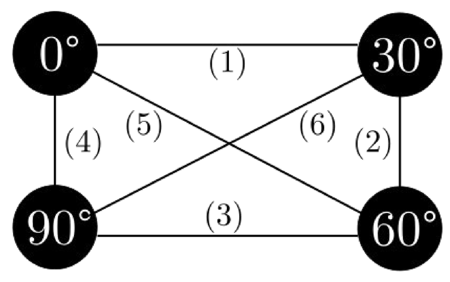


→ Errors over iterations highlight better generalisation using an hypernetwork in low data regimes

→ Finetuning the Hypernetwork helps at reducing variance on the errors leading to a less biased and more generalized model

Methodology

Datasets split



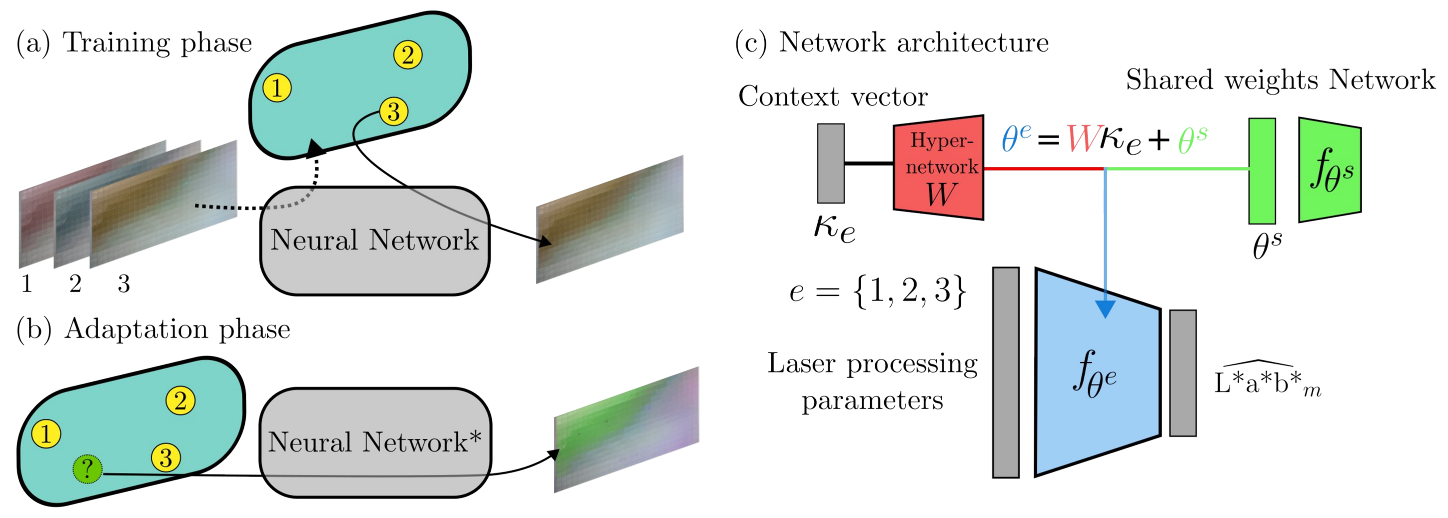
Path	ΔE94 T	ΔE94 BR
(1)	1.28±0.72	3.13±1.93
(2)	1.21±0.76	2.14±1.32
(3)	1.01±0.78	1.99±1.20
(4)	2.08±1.36	3.90±2.24
(5)	1.94±1.13	4.27±2.75
(6)	1.60±1.14	2.26±1.22

Dataset is split along polarization angles to create 4 unique environments of 2400 samples for T and BR

Model training (Adapted from [5])

Train/valid/test = 80/10/10 wrt. processing parameters

3 environments are given into training



f_{θ^e}: $\mathcal{X} \rightarrow \mathcal{Y}$ is a MLP, $\mathcal{X} \in \mathbb{R}^4$: laser processing parameters and $\mathcal{Y} \in \mathbb{R}^3$: CIE Lab, W is a linear projector.

Learnt model adapts to the test environment

Only $\kappa_e \in \mathbb{R}^3$ needs to be updated for adaptation

The optimization problem is defined as :

$$\min_{\theta^s, W, \{\kappa_e\}_{e \in \mathcal{E}_{tr}}} \sum_{e \in \mathcal{E}_{tr}} (\mathcal{L}(\theta^s + W\kappa_e, \mathcal{D}_e) + \lambda_\kappa ||\kappa_e||_2^2 + \lambda_W \sum_{i=1}^{d_\theta} ||W_{i,:}||^2$$

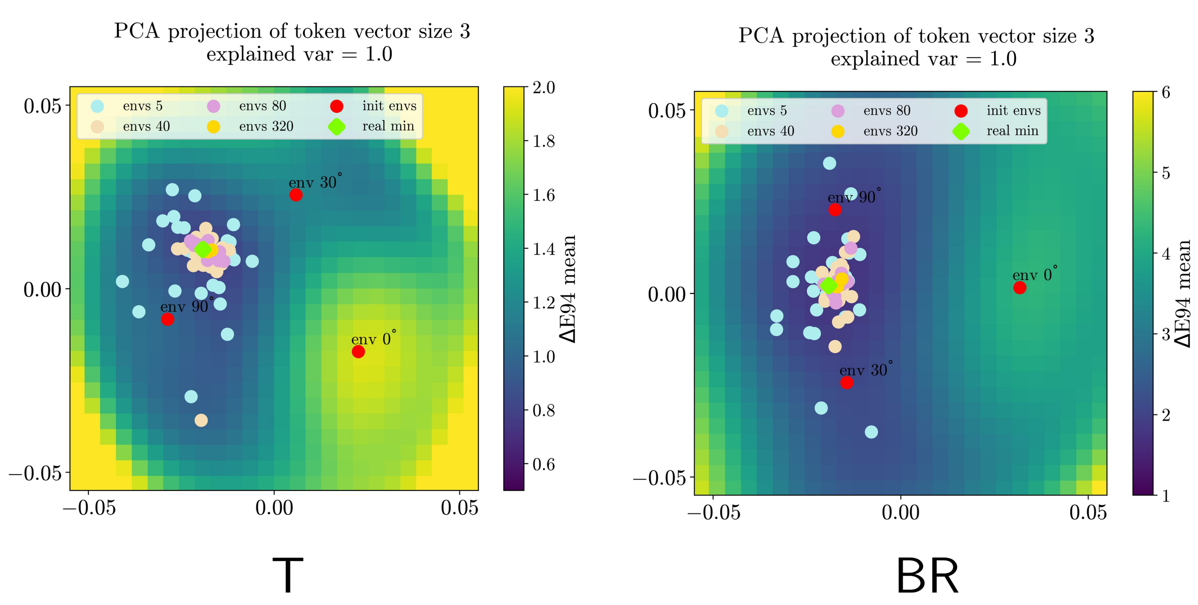
$\mathcal{D}$e is a set of samples from $\mathcal{X}$x$\mathcal{Y}$ from a specific environment e

$\mathcal{L}$ is the ΔE_{94} a perceptual color distance metric

Qualitative Results

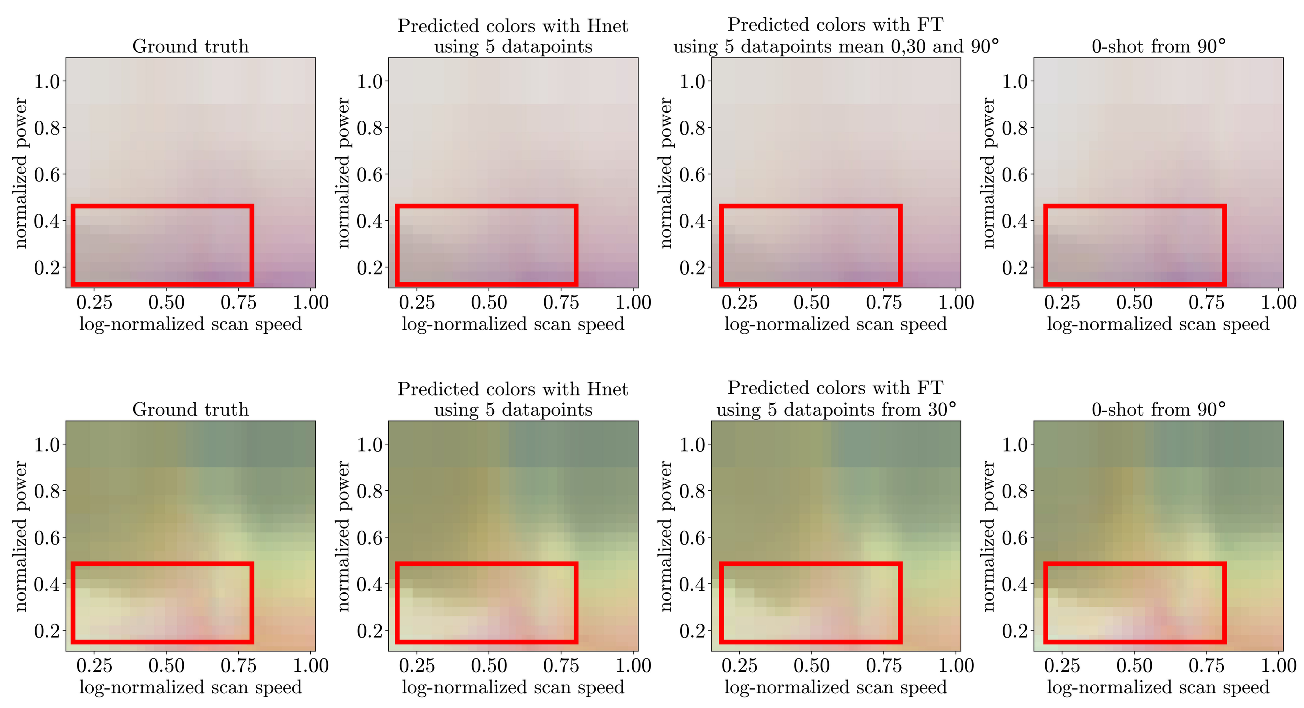
Learned Context Vectors maps show datasets organisation and convergence to global optimum

(Error maps for adaptation toward 60°)



Hypernetwork tends to better preserve color variation structures

(Depicted here by the portion highlighted by a red square)



Conclusion

→ Learning jointly several experimental datasets helps for adaptation to new experimental processing cases

→ PCA map provides insights on how adaption is performed based on known training environments

$\Longrightarrow$ Linked Context vectors to real physical measurements (optical response, nanoparticles distribution etc...)

References

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[5] Kirchmeyer et al., Generalizing to New Physical Systems via Context-Informed Dynamics Model. ICML (2022)

[6] De Mathelin et al., Adversarial Weighting for Domain Adaptation in Regression. ICTAI (2021)

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