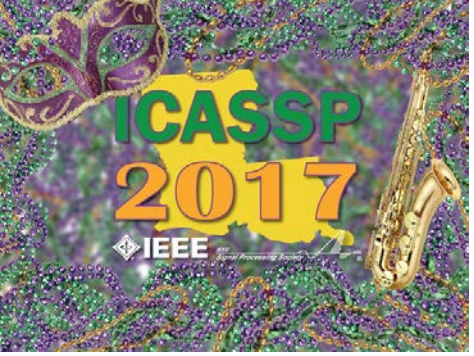

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UNIQUE: Unsupervised Image Quality Estimation

D.Temel, M. Prabhushankar, and G. AlRegib

Center for Signal and Information Processing
School of Electrical and Computer Engineering
Georgia Institute of Technology
Atlanta, GA

Georgia Tech

Outline

I. Introduction

II. Literature Review

III. UNIQUE: Unsupervised Image Quality Estimation

- *Overview of UNIQUE*
- *Unsupervised Learning Mechanism*
- *Preprocessing*
- *Visualization*

V. Validation

VI. Conclusion

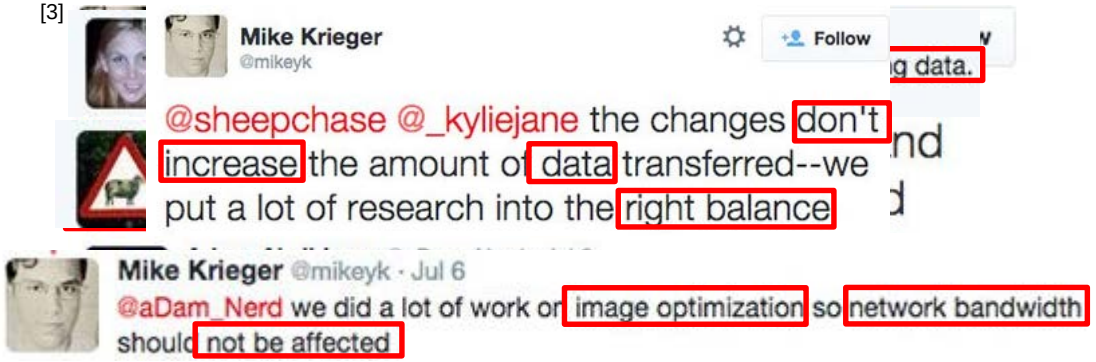
I. Introduction

Image Quality Assessment : Why?

Application	Average daily shared photos [1]
	390 Million
	700 Million
	70 Million
	760 Million

[2]

[3]



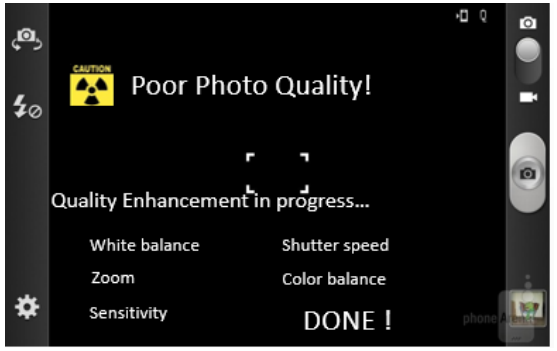
YouTube

NETFLIX

HBO

Remote Assistance

Smart Capturing



[1] Adweek, http://www.adweek.com/socialtimes/how-many-photos-are-uploaded-to-snapchat-every-second/621488, Jun 2015
[2]LG, "Ultra Clarity, Ultra Scale," http://www.lg.com/levant_en/Mini-page-ultra/index
[3] PetPixel, http://petapixel.com/2015/07/08/instagram-resolution-increase-heres-how-it-affects-image-quality-and-file-size/, July 8, 2015

I. Introduction

Image Quality Assessment : In Practice

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Test setup

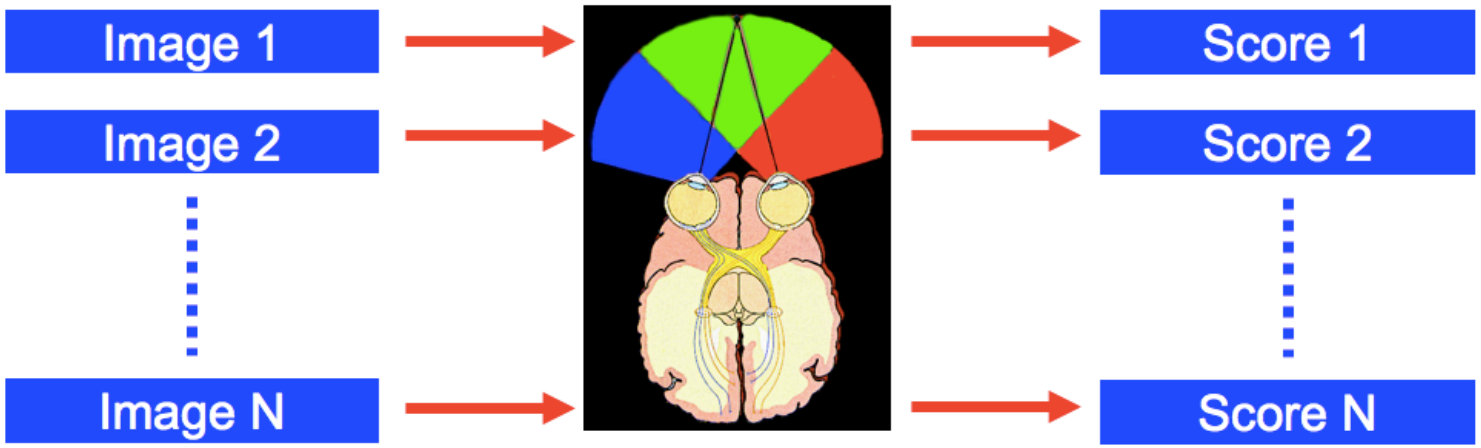
Reference images [1]

Distorted images [1]

Subjective Scores

5 → Very Good

no perceived distortion



Mean opinion scores

[1] Sheikh, H.R., Wang, Z., Cormack, L. and Bovik, A.C., "LIVE Image Quality Assessment Database Release 2", http://live.ece.utexas.edu/research/quality.

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II. Literature Review

Data-driven Image Quality Estimators

YEAR		2011		2012			2013			2014				2015					2016	
QUALITY ESTIMATORS		LBIQ	DIIVINE	CORNIA	BRISQUE	MLIQM	CB/SF	QAC	SPARQ	Tang	QAF	Kang	Q_{area} $Q_{exponent}$	IQA-CNN++	Li	S^2F^2	DLIQA	Gao	CNN-SVR	UNIQUE
Visual system			■		■	■		■	■						■	■	■	■		■
Color						■														■
Do not require	Distortion specific data in the training								■				■							■
	Labels in the training							■	■				■							■
	Handcrafting features			■			■					■		■					■	■

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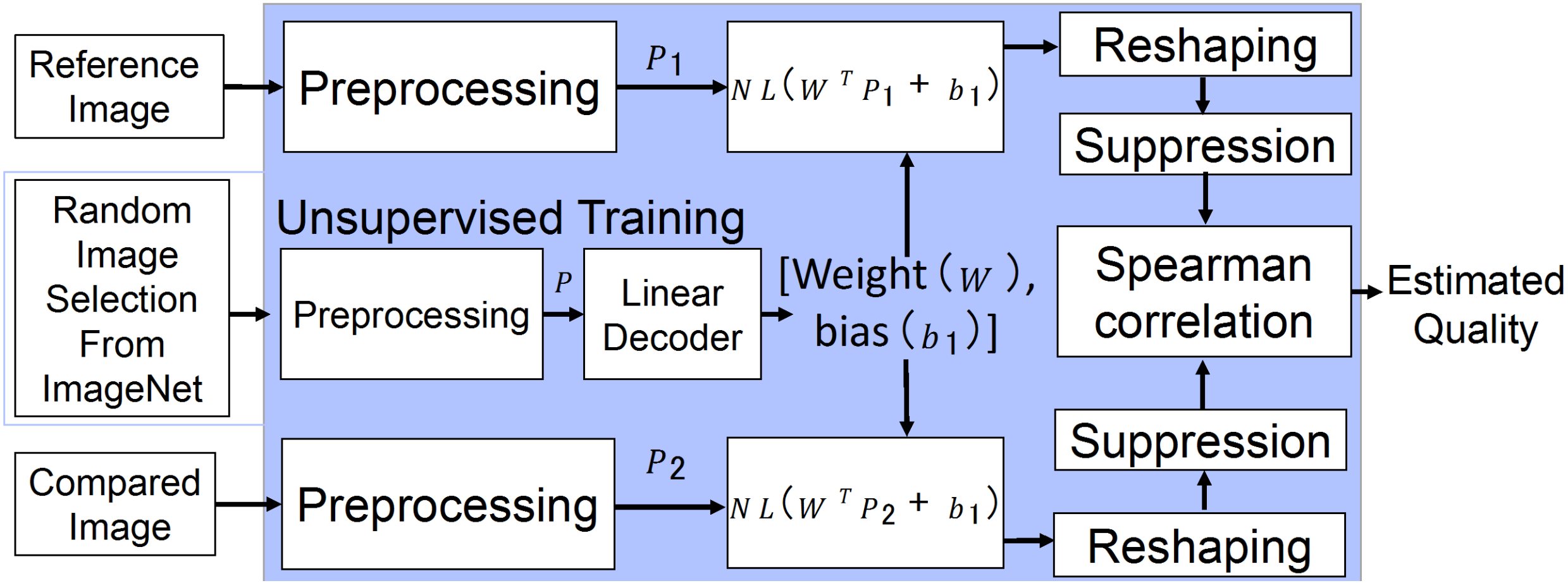
III. UNIQUE: Unsupervised Image Quality Estimation

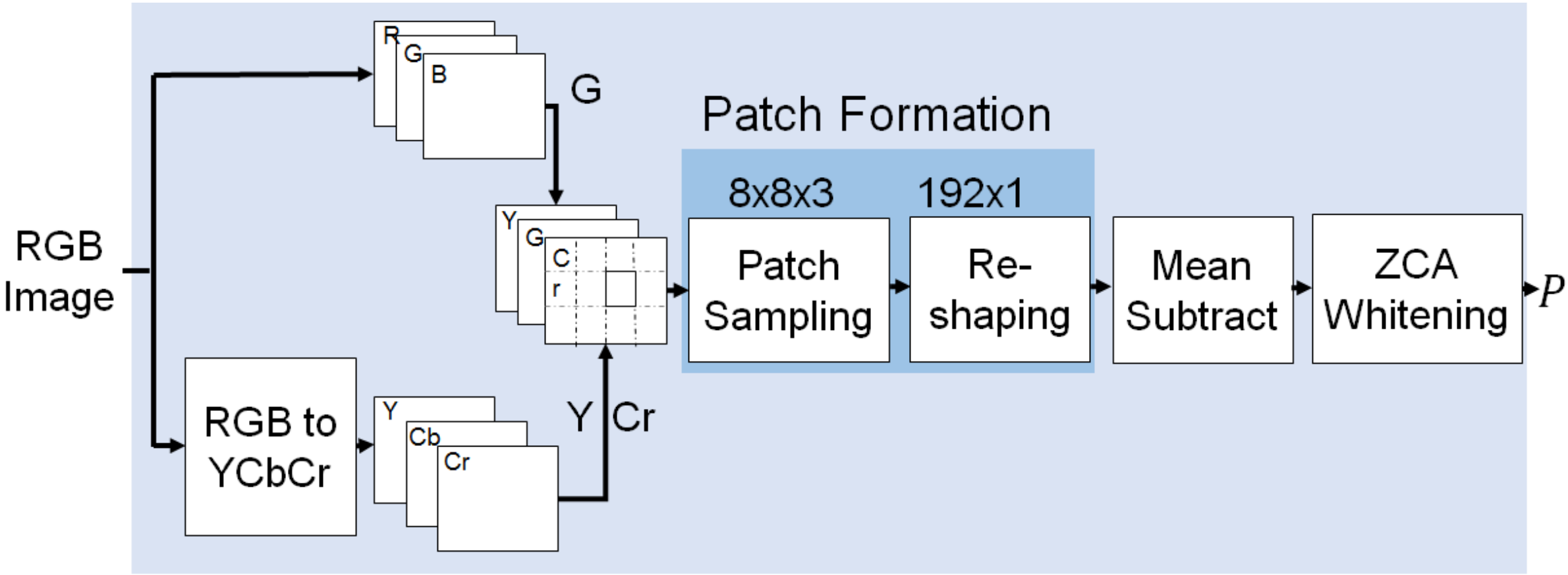
Overview of UNIQUE



D. Temel, M. Prabhushankar, and G. AlRegib, "UNIQUE: Unsupervised Image Quality Estimation," the *IEEE Signal Processing Letters*, vol.23, no.10, pp.1414-1418.

III. UNIQUE: Unsupervised Image Quality Estimation

Preprocessing

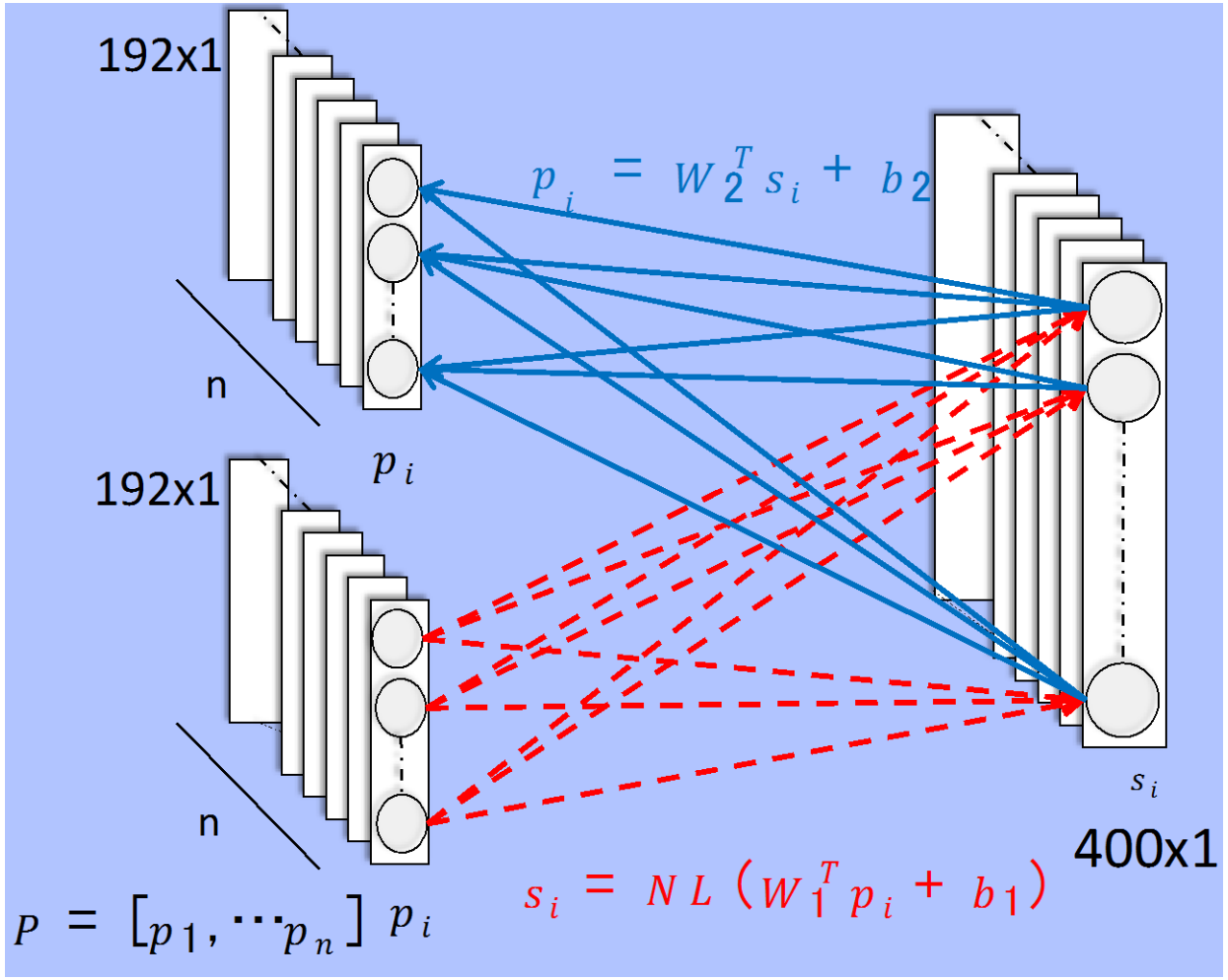


D. Temel, M. Prabhushankar, and G. AlRegib, "UNIQUE: Unsupervised Image Quality Estimation," the *IEEE Signal Processing Letters*, vol.23, no.10, pp.1414-1418.

III. UNIQUE: Unsupervised Image Quality Estimation

Unsupervised Learning Mechanism

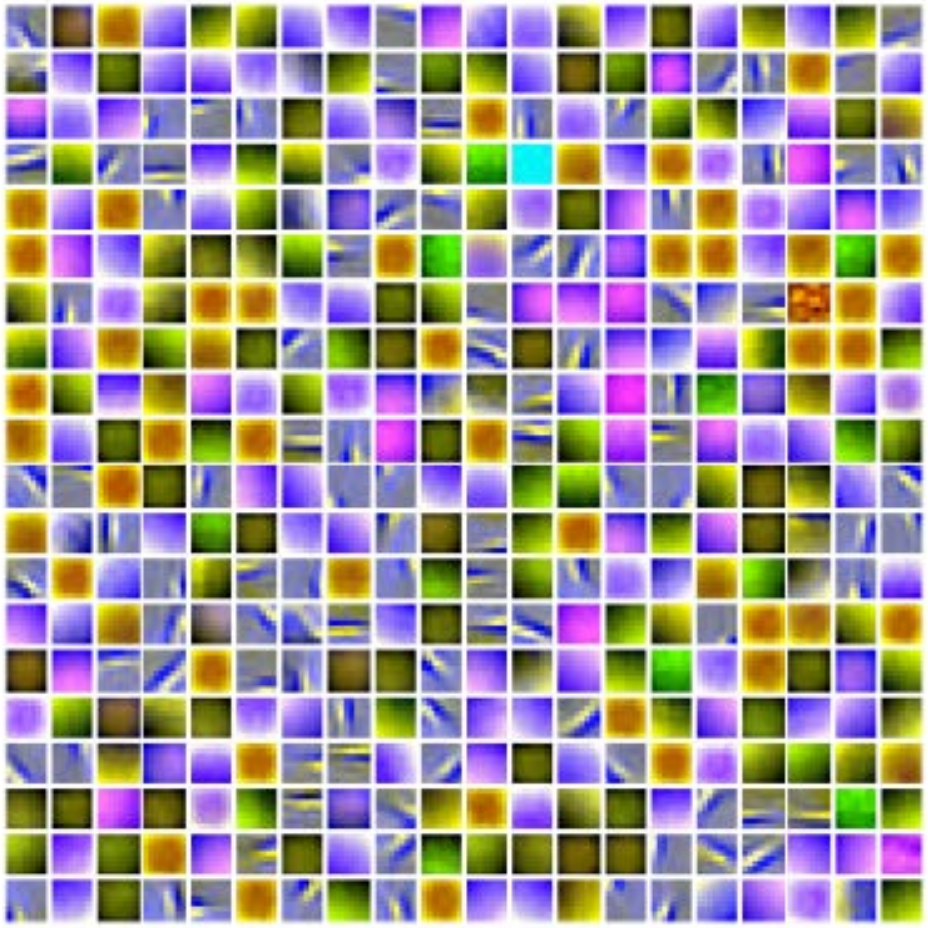
$$J(W_1, W_2, b_1, b_2) = \|(W_2^T s + b_2) - P\|_2^2 + \beta\|s\|_1 + \lambda\|W\|_2^2,$$



D. Temel, M. Prabhushankar, and G. AlRegib, "UNIQUE: Unsupervised Image Quality Estimation," the *IEEE Signal Processing Letters*, vol.23, no.10, pp.1414-1418.

III. UNIQUE: Unsupervised Image Quality Estimation

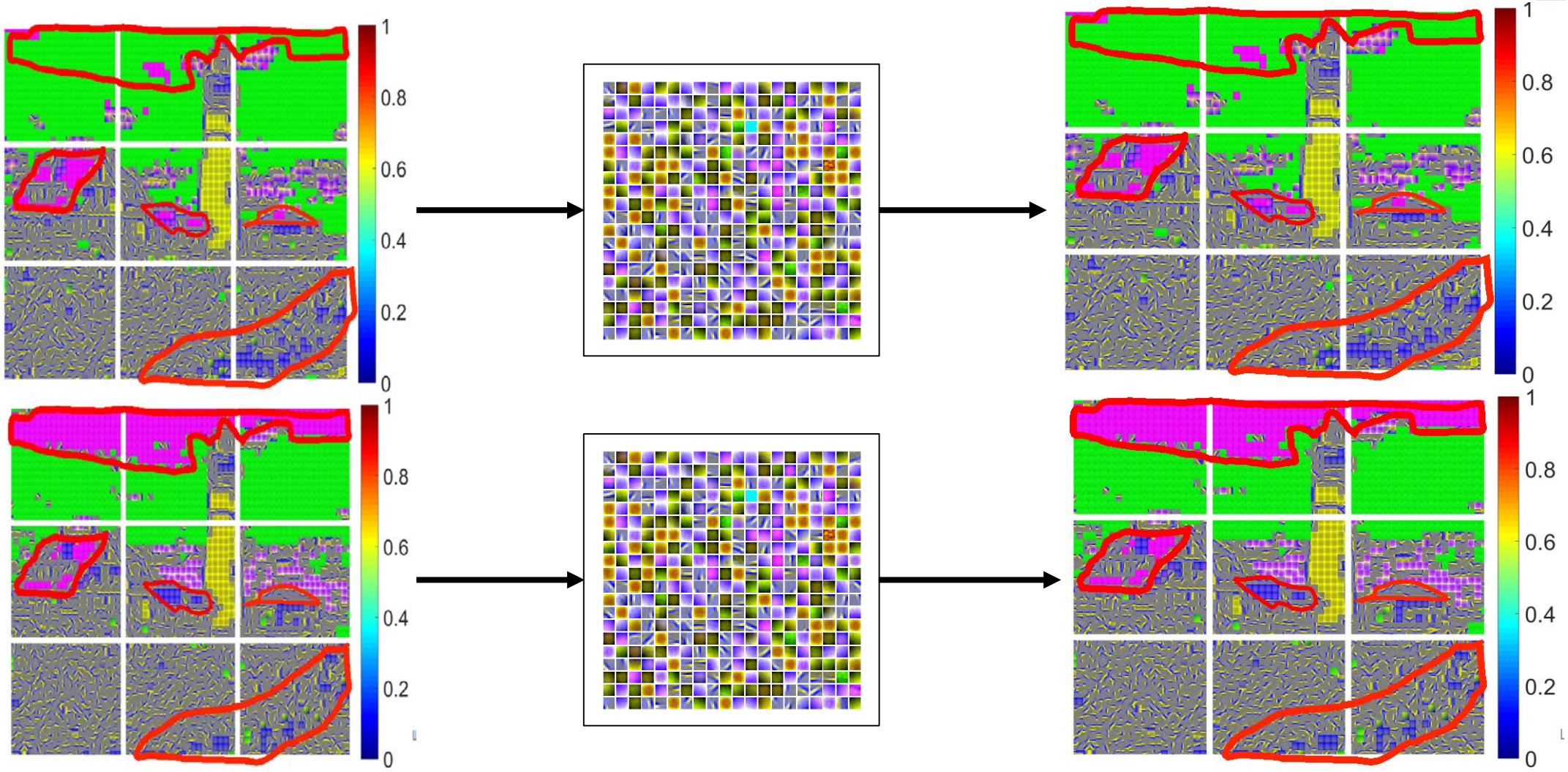
Visualization of Learnt Filters



D. Temel, M. Prabhushankar, and G. AlRegib, “UNIQUE: Unsupervised Image Quality Estimation,” the *IEEE Signal Processing Letters*, vol.23, no.10, pp.1414-1418.

III. UNIQUE: Unsupervised Image Quality Estimation

Visualization of Processed Images



D. Temel, M. Prabhushankar, and G. AlRegib, “UNIQUE: Unsupervised Image Quality Estimation,” the *IEEE Signal Processing Letters*, vol.23, no.10, pp.1414-1418.

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V. Image Quality Estimators

- *Validation*

Databases

	LIVE	MULTI	TID	Total
Compression	460	180	375	1015
Image Noise	174	180	1375	1729
Communication	174		250	424
Blur	174	315	250	739
Color	-		375	375
Global	-		250	250
Local	-		250	250

LIVE database

TID 2013 database

Performance Metrics

Root mean square error (RMSE) *Accuracy*	*Outlier Ratio (OR)* *Consistency*	*Pearson Linear Correlation Coefficient (PLCC)* *Linearity*	*Spearman Rank Correlation Coefficient (SRCC)* *Ranking*
$\sqrt{E[X-Y]^2}$	$\frac{N_{outliers}}{N_{total}}$	$\frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y}$	$X_i, Y_i \longrightarrow x_i, y_i$ $1-\frac{6\sum_{i=1}^{N}(x_i-y_i)^2}{N(N^2-1)}$

V. Image Quality Estimators

- *Validation*

TABLE I: Performance of image quality estimators.

Methods	PSNR	PSNR HA [20]	PSNR HMA [20]	SSIM [12]	MS SSIM [21]	CW SSIM [22]	IW SSIM [23]	SR SIM [24]	FSIMc [25]	PerSIM [26]	BRISQUE [7]	BIQI [8]	BLIINDS2 [9]	UNIQUE
	Outlier Ratio													
MULTI	0.008	0.013	0.008	0.015	0.013	0.093	0.013	**0**	0.015	0.004	0.068	0.024	0.077	**0**
TID13	0.725	**0.615**	0.670	0.733	0.691	0.855	0.700	**0.632**	0.727	0.655	0.851	0.855	0.851	0.639
	Root Mean Square Error													
LIVE	8.61	6.93	**6.58**	7.52	7.44	11.2	7.11	7.54	7.20	6.80	8.57	10.8	9.049	**6.76**
MULTI	12.7	11.3	10.7	11.0	11.2	18.8	10.0	**8.68**	10.7	9.89	15.0	12.7	17.4	**8.35**
TID13	0.87	0.65	0.69	0.76	0.69	1.20	0.68	**0.61**	0.68	0.64	1.10	1.10	1.09	**0.60**
	Pearson Correlation Coefficient													
LIVE	0.928 (-1)	0.953 (0)	**0.958 (0)**	0.945 (-1)	0.946 (-1)	0.872 (-1)	0.951 (0)	0.945 (-1)	0.950 (0)	0.955 (0)	0.928 (-1)	0.883 (-1)	0.920 (-1)	**0.956 Ref**
MULTI	0.739 (-1)	0.801 (-1)	0.821 (-1)	0.812 (-1)	0.802 (-1)	0.379 (-1)	0.847 (-1)	**0.888 (0)**	0.821 (-1)	0.852 (-1)	0.605 (-1)	0.738 (-1)	0.389 (-1)	**0.897 Ref**
TID13	0.705 (-1)	0.850 (-1)	0.827 (-1)	0.788 (-1)	0.830 (-1)	0.227 (-1)	0.831 (-1)	**0.866 (0)**	0.832 (-1)	0.854 (-1)	0.460 (-1)	0.448 (-1)	0.473 (-1)	**0.870 Ref**
	Spearman Correlation Coefficient													
LIVE	0.909 (-1)	0.937 (-1)	0.944 (0)	0.949 (0)	0.951 (0)	0.902 (-1)	**0.960 (1)**	0.955 (0)	**0.959 (0)**	0.950 (0)	0.939 (-1)	0.897 (-1)	0.922 (-1)	0.952 Ref
MULTI	0.677 (-1)	0.714 (-1)	0.743 (-1)	0.860 (0)	0.836 (0)	0.630 (-1)	**0.883 (0)**	**0.866 (0)**	**0.866 (0)**	0.818 (-1)	0.598 (-1)	0.610 (-1)	0.386 (-1)	**0.866 Ref**
TID13	0.700 (-1)	0.847 (0)	0.817 (-1)	0.741 (-1)	0.785 (-1)	0.562 (-1)	0.777 (-1)	0.807 (-1)	0.851 (0)	**0.853 (0)**	0.414 (-1)	0.393 (-1)	0.396 (-1)	**0.860 Ref**

V. Image Quality Estimators

- *Validation*

TABLE II: Distributional difference between subjective scores and objective quality estimates.

Metric	Difference-LIVE					Difference-MULTI					Difference-TID13				
	EMD	KL	JS	HI	L2	EMD	KL	JS	HI	L2	EMD	KL	JS	HI	L2
IW-SSIM	0.29	0.32	0.07	0.29	0.07	0.42	0.47	0.09	0.42	0.11	0.50	1.67	0.19	0.50	0.18
SR-SIM	0.32	0.38	0.08	0.32	0.08	0.40	0.42	0.09	0.40	**0.10**	0.50	1.62	0.19	0.50	0.17
FSIMc	0.27	0.30	0.06	0.27	0.07	0.45	0.51	0.11	0.45	0.11	0.68	2.54	0.30	0.68	0.23
UNIQUE	**0.23**	**0.25**	**0.05**	**0.23**	**0.06**	**0.35**	**0.36**	**0.07**	**0.35**	**0.10**	**0.39**	**0.87**	**0.12**	**0.39**	**0.11**

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Contributions and Observations

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YEAR		2011		2012			2013			2014				2015					2016	
QUALITY ESTIMATORS		LBIQ	DIIVINE	CORNIA	BRISQUE	MLIQM	CB/SF	QAC	SPARQ	Tang	QAF	Kang	Q_{area} $Q_{exponent}$	IQA-CNN++	Li	S^2F^2	DLIQA	Gao	CNN-SVR	UNIQUE
Visual system			■		■	■		■	■						■	■	■	■		■
Color						■														■
Do not require	Distortion specific data in the training								■				■							■
	Labels in the training							■	■				■							■
	Handcrafting			■			■					■		■					■	■

To measure perceived quality

- Hand-crafting is not sufficient, we should also ***learn*** from the data.
- Labels are not easy to find, we need to focus more on ***unsupervised*** approaches.
- ***Color perception*** must be included in a comprehensive visual system model.
- The best example is our ***visual system***, we should model it as much as we can.

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Thank You!

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Backup Slides

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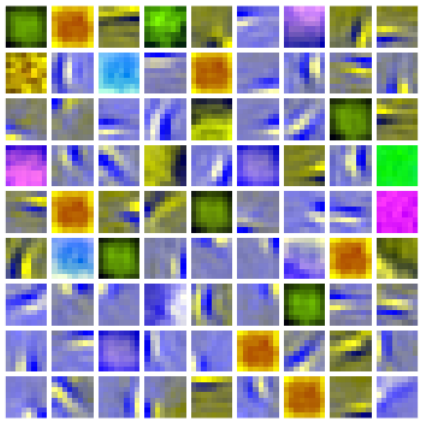
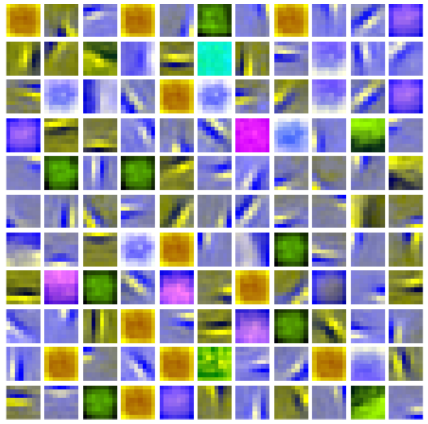
IV. MS-UNIQUE: Multi-model and Sharpness-weighted UNIQUE

Multi-model

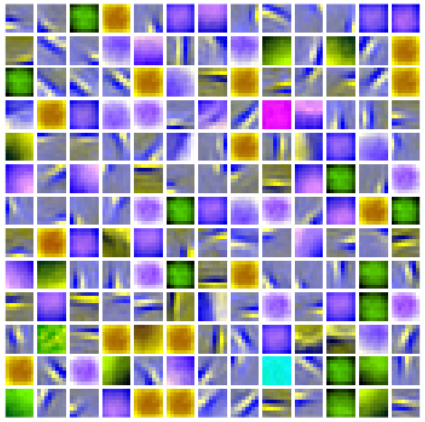
Varying the number of neurons to learn global and local features



81



121



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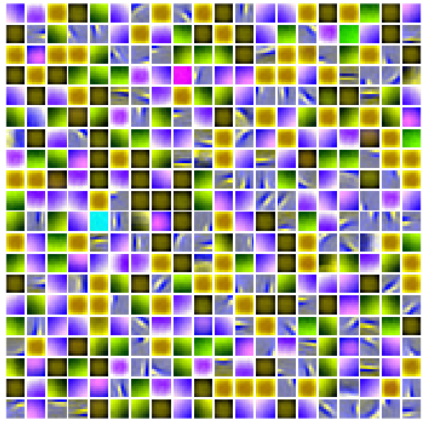

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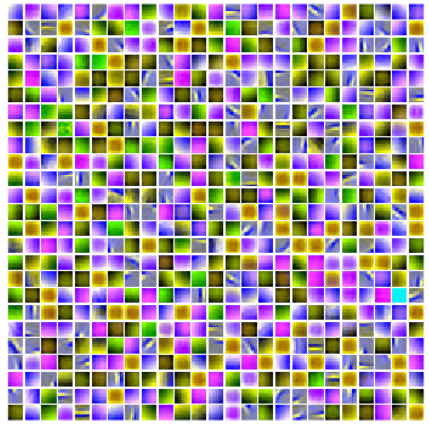
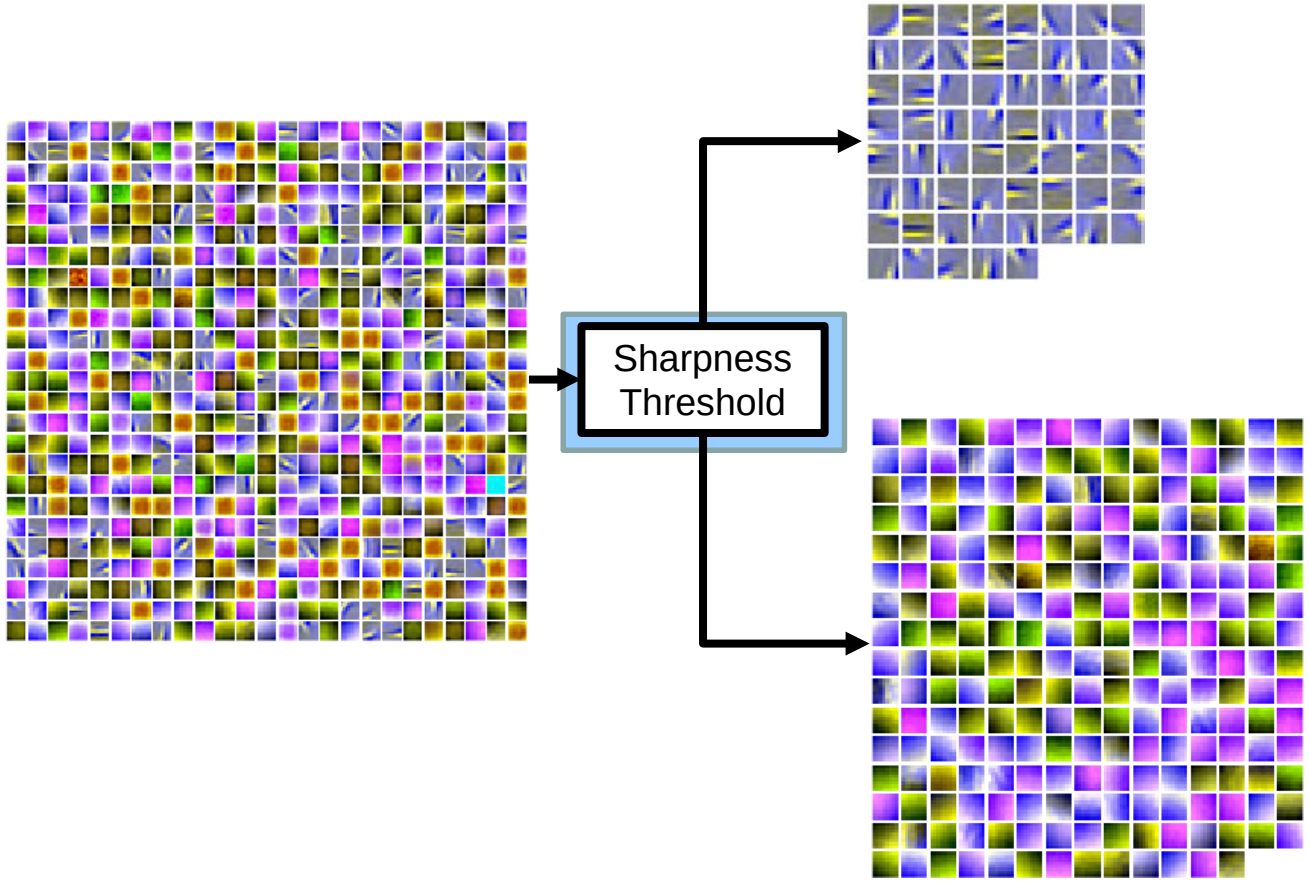
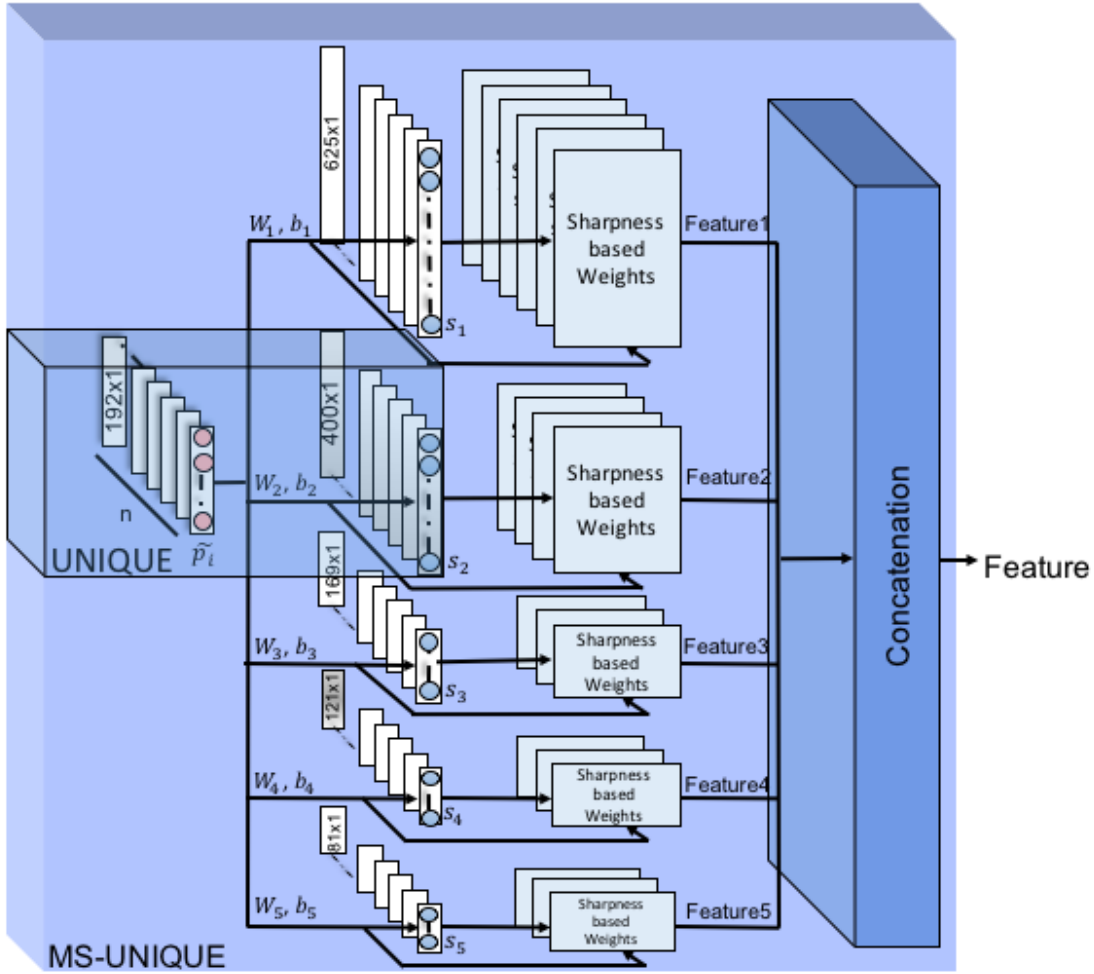


625

IV. MS-UNIQUE: Multi-model and Sharpness-weighted UNIQUE

Sharpness-weighted Multi-model





IV. MS-UNIQUE: Multi-model and Sharpness-weighted UNIQUE

Visualization

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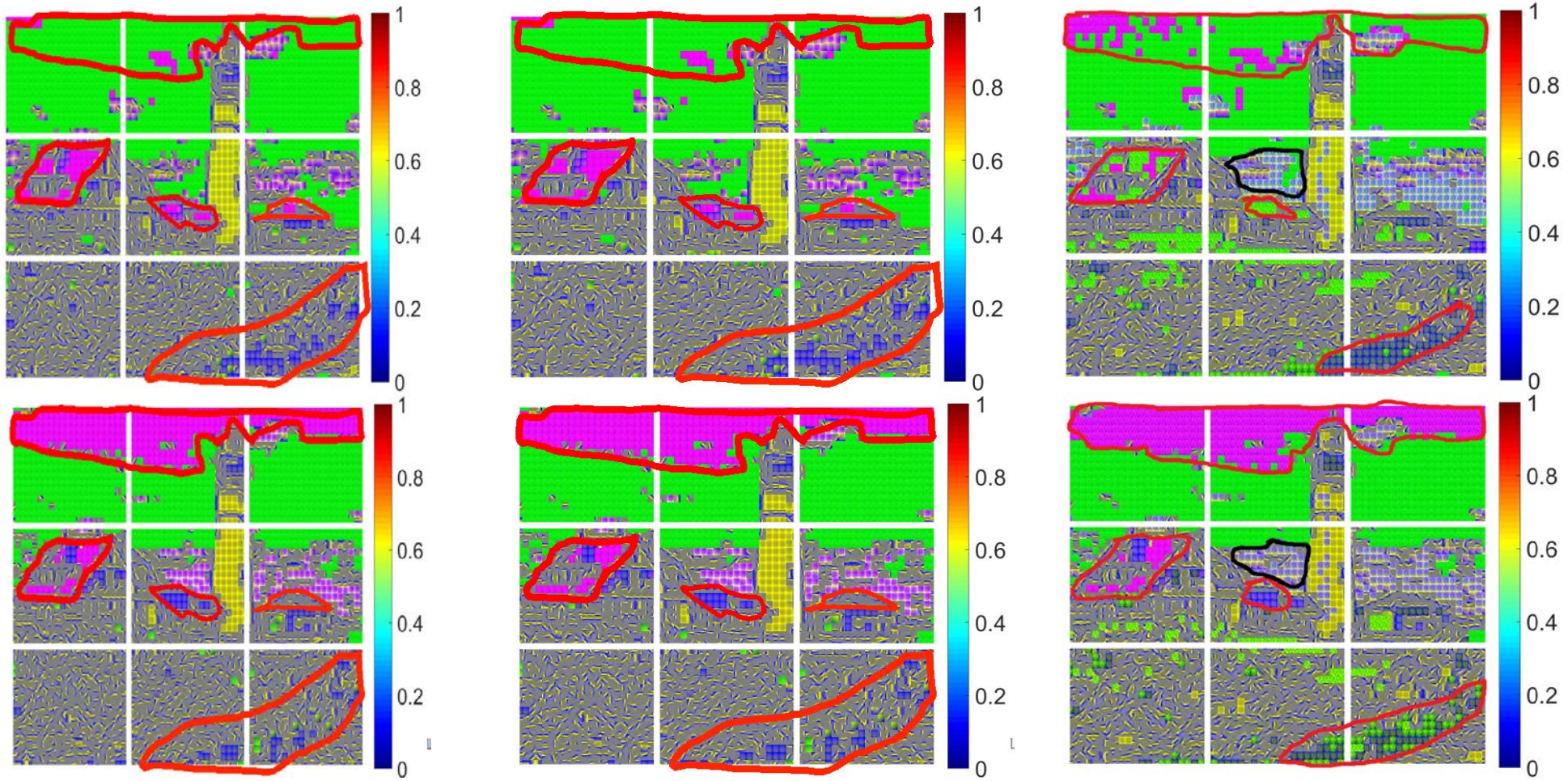
Images

UNIQUE

MS-UNIQUE



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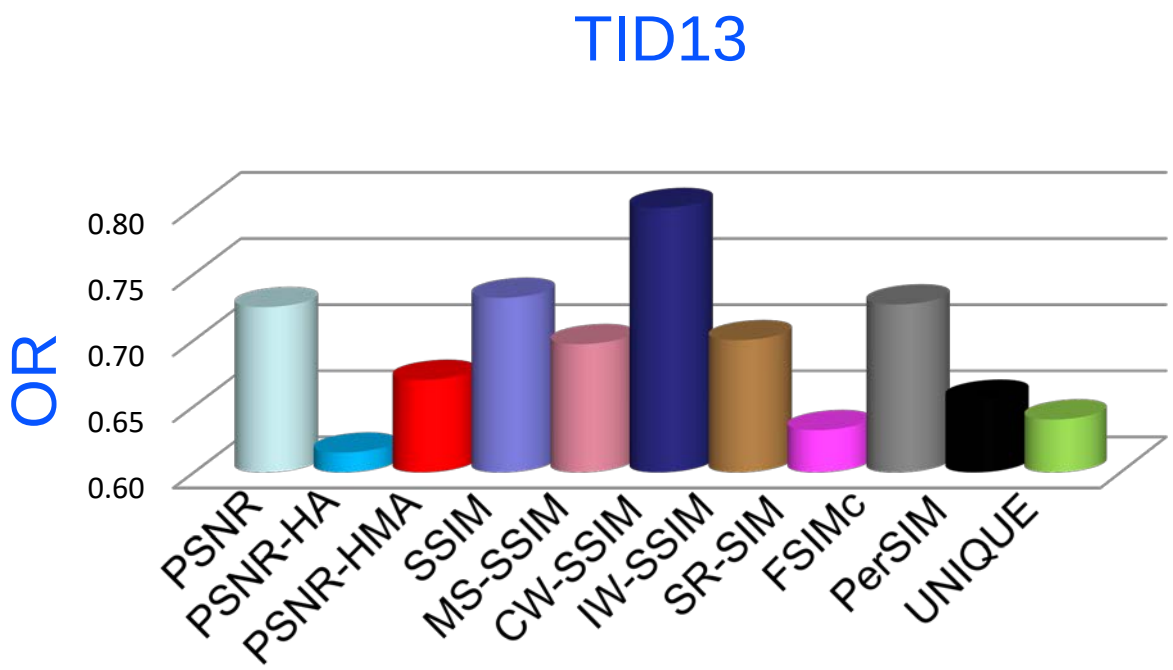
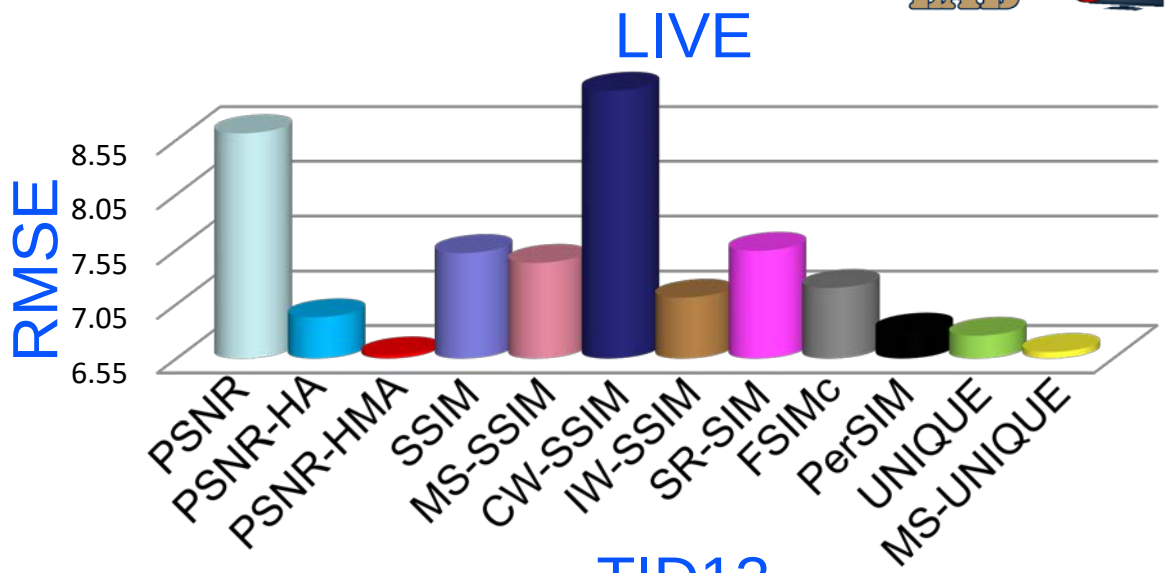
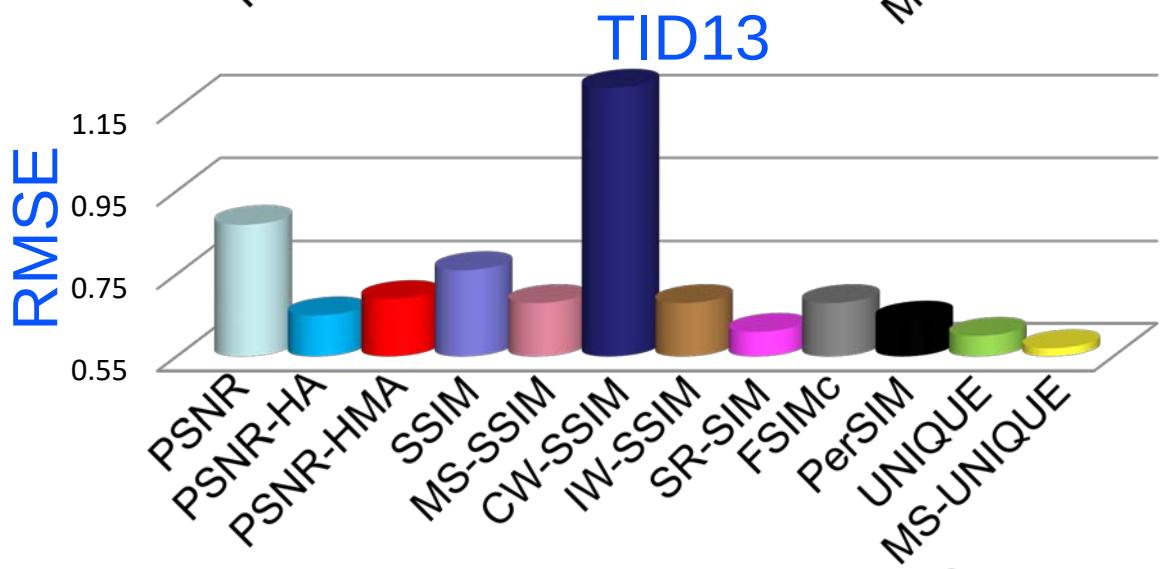
V. Image Quality Estimators

- *Validation*







V. Image Quality Estimators

- *Validation*