Analysis of Orientation and Scale in Smoothly Varying Textures

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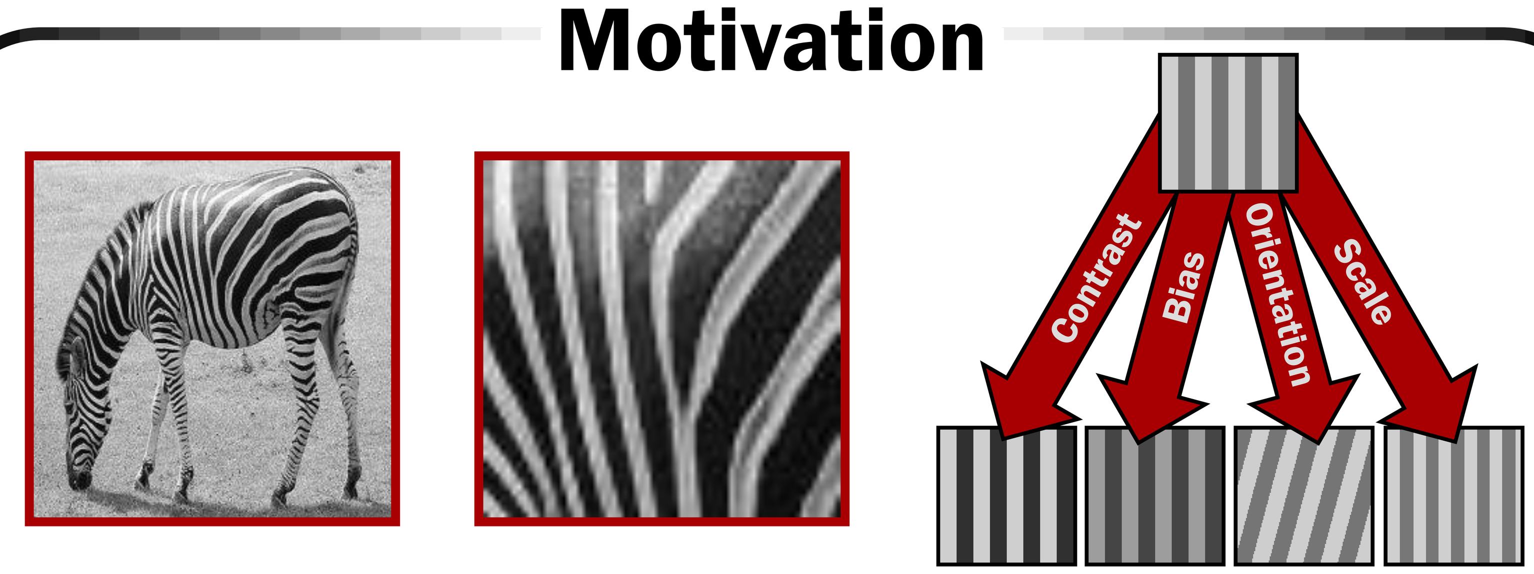
Motivation

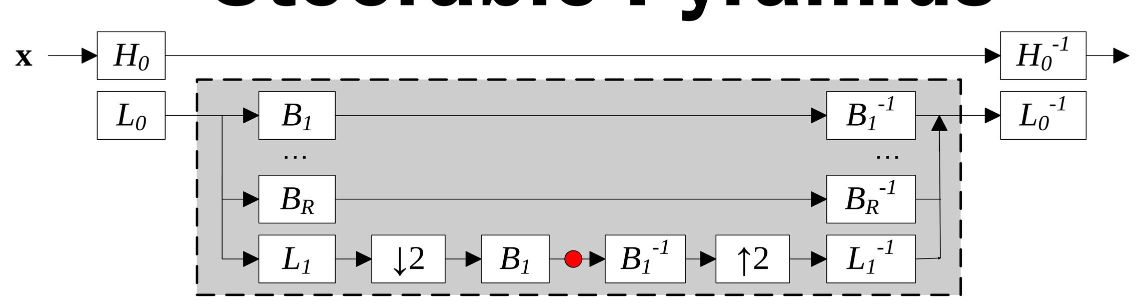


Goal: Decomposition of textured image regions into four intrinsic properties by modeling smooth variations in orientation and scale.

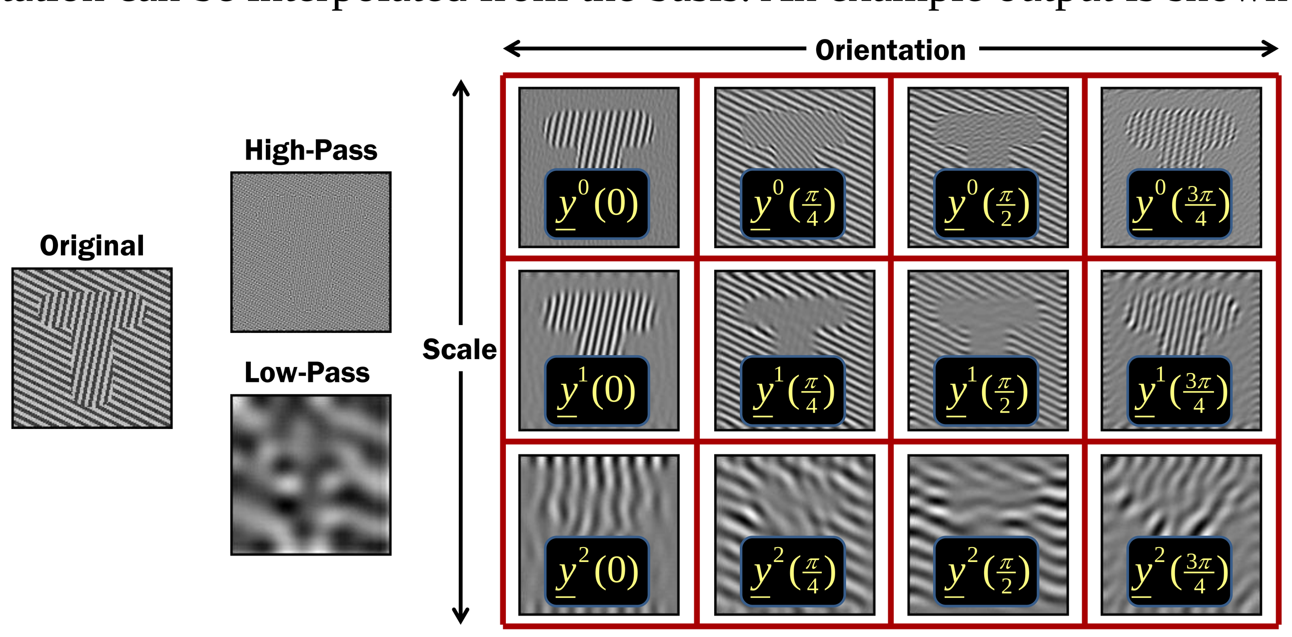
- Utilize steerable pyramid analysis [6] as a base representation.
- Decompose texture into four local attributes: contrast, bias, orientation and scale.
- Capture smoothness via Markov random fields.
- Incorporate physical imaging phenomenon for natural scenes.

Results: Demonstrate utility for unsupervised segmentation, reflectance & shading estimation, and estimation of radiometric response function from a single image.

Steerable Pyramids



The steerable pyramid [6] is a multi-scale and multi-orientation decomposition of an image. The red dot is recursively replaced with the gray box. The output at any orientation can be interpolated from the basis. An example output is shown below.

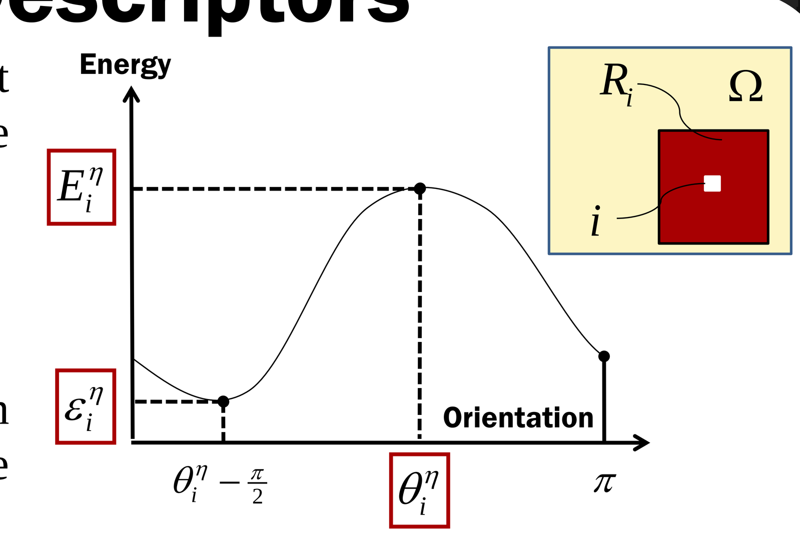


Texture Descriptors

For the interpolated filter output, $y_i^\eta(\theta)$ at pixel i, scale η, and orientation θ, we define the angular energy as:

$$E_i^\eta(\theta) = \frac{1}{|R_i^\eta|} \sum_{j \in R_i^\eta} \left| y_j^\eta(\theta) \right|^2$$

A plot of the angular energy as a function of orientation is shown on the right. The extracted features are boxed.



We also define the average intensity of the texture at a given scale as:

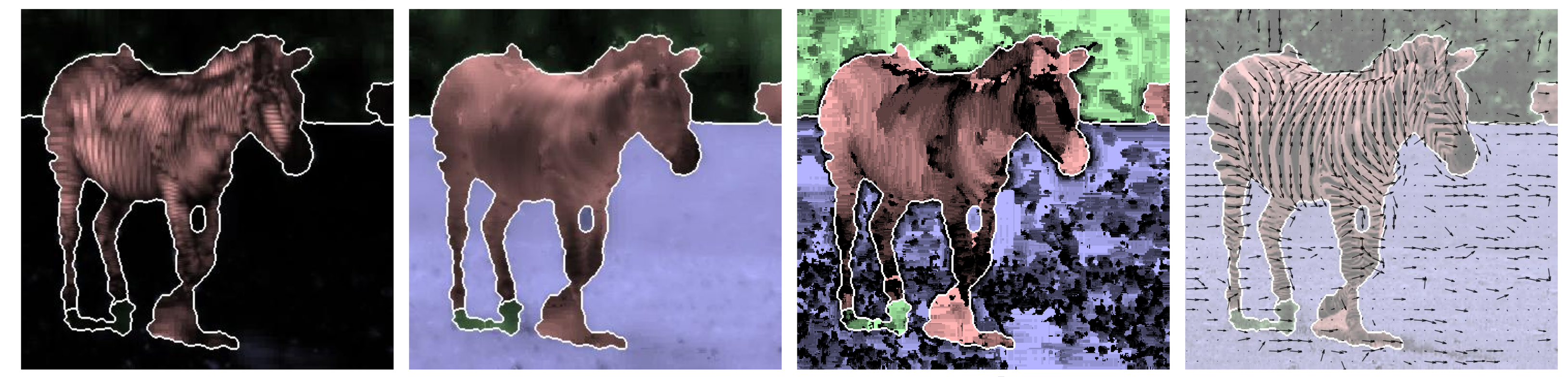
$$\mu_i^\eta = \frac{1}{|R_i^\eta|} \sum_{j \in R_i^\eta} x_j$$

Our final feature set is shown in the table to the right.

Feature Set	
$\eta_i = \arg\max_\eta E_i^\eta$	Scale
$E_i = E_i^{\eta_i}$	Contrast Energy
$\varepsilon_i = \varepsilon_i^{\eta_i}$	Residual (Orthogonal) Energy
$\theta_i = \theta_i^{\eta_i}$	Orientation
$\mu_i = \mu_i^{\eta_i}$	Average Intensity

Feature Visualization

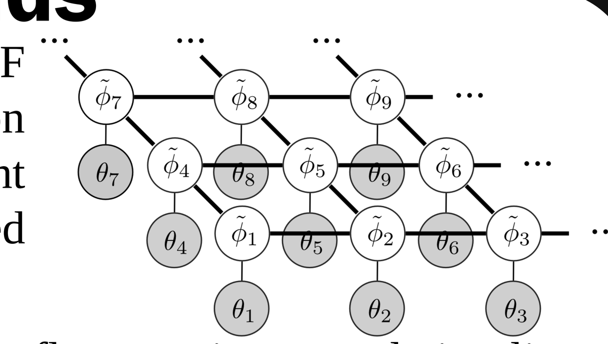
The following images show the measured features after segmentation.



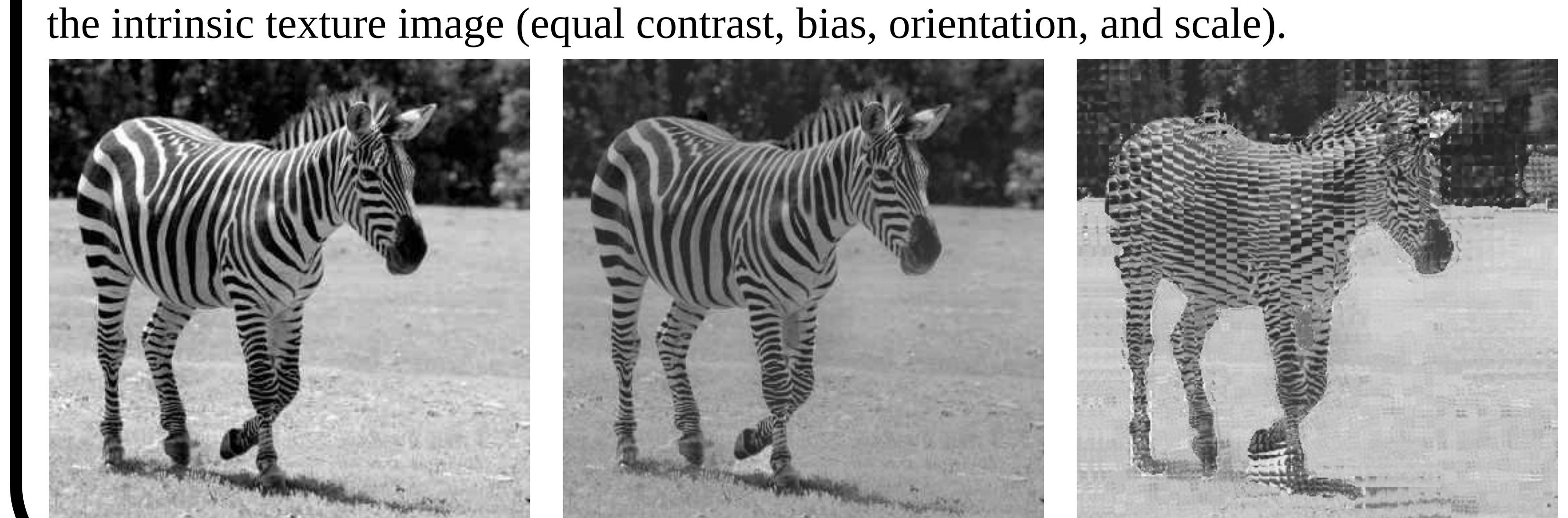
Contrast Energy | Bias | Scale (brighter is coarser) | Orientation

Smooth Fields

For each feature, we impose a smooth, additive MRF with a nonparametric noise model. In the orientation case, this is represented as the diagram to the right where $\tilde{\phi}$ is the smooth field. The MRFs are estimated using a fast fixed-point update.



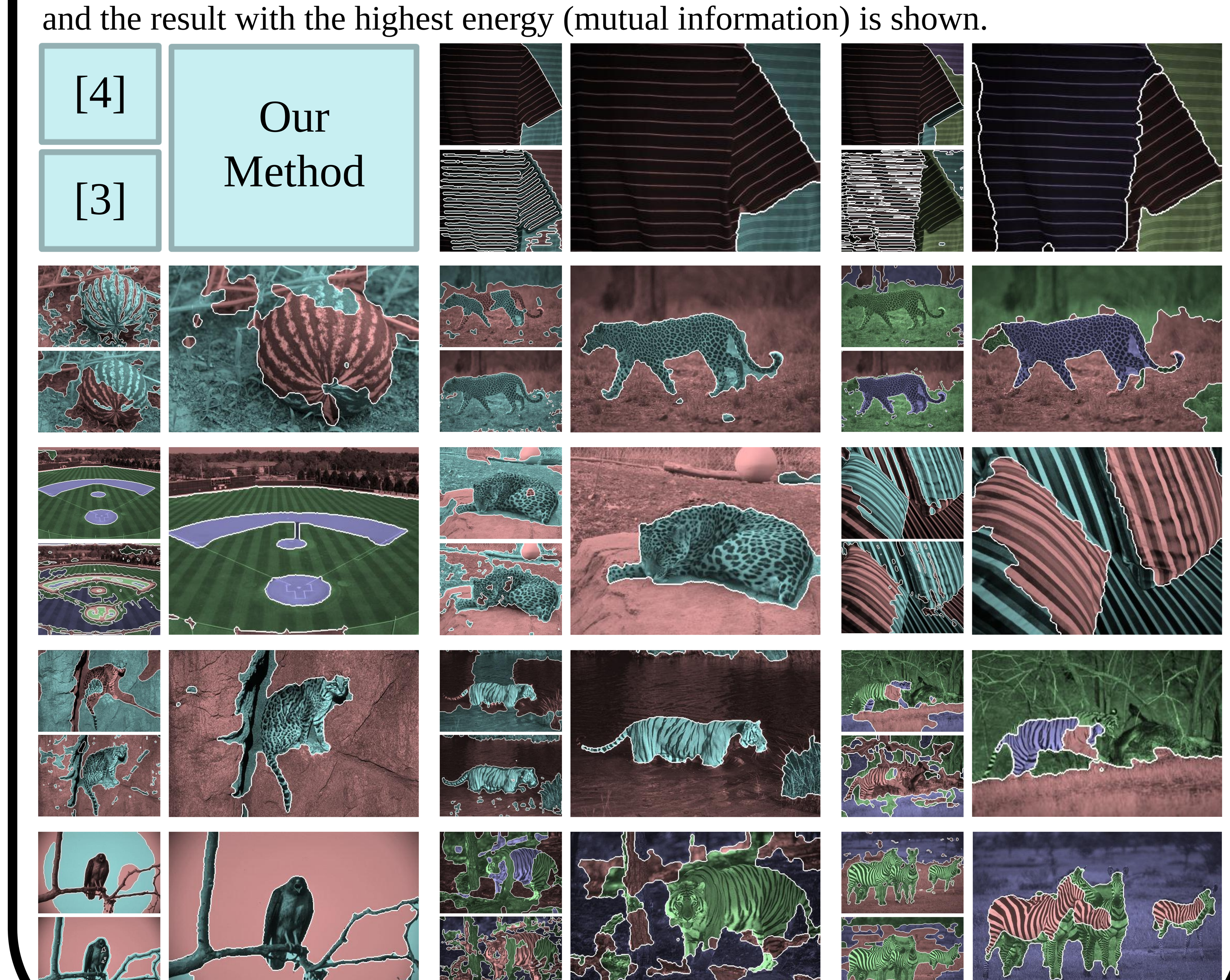
Once these fields are found, we can find the intrinsic reflectance image and visualize the intrinsic texture image (equal contrast, bias, orientation, and scale).



Original Image | Intrinsic Reflectance Image | Intrinsic Texture Image

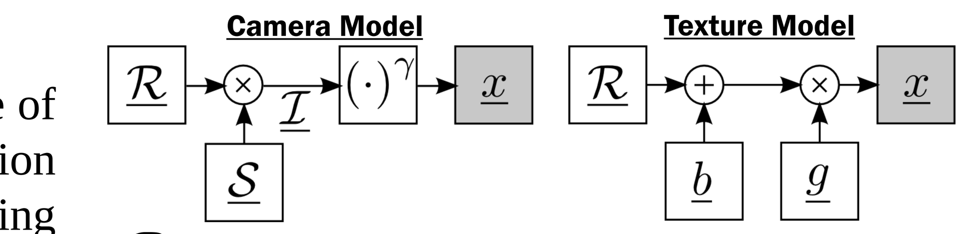
Segmentation

We use our texture representation in the segmentation algorithm of [4], incorporating the multi-region segmentation algorithm used in [1]. The number of regions is specified for each image. We alternate between level-set based segmentation and MRF estimation. Inclusion of the smooth field assumptions improves [3] & [4], otherwise they perform poorly on these scenes. Eight random initializations are used and the result with the highest energy (mutual information) is shown.



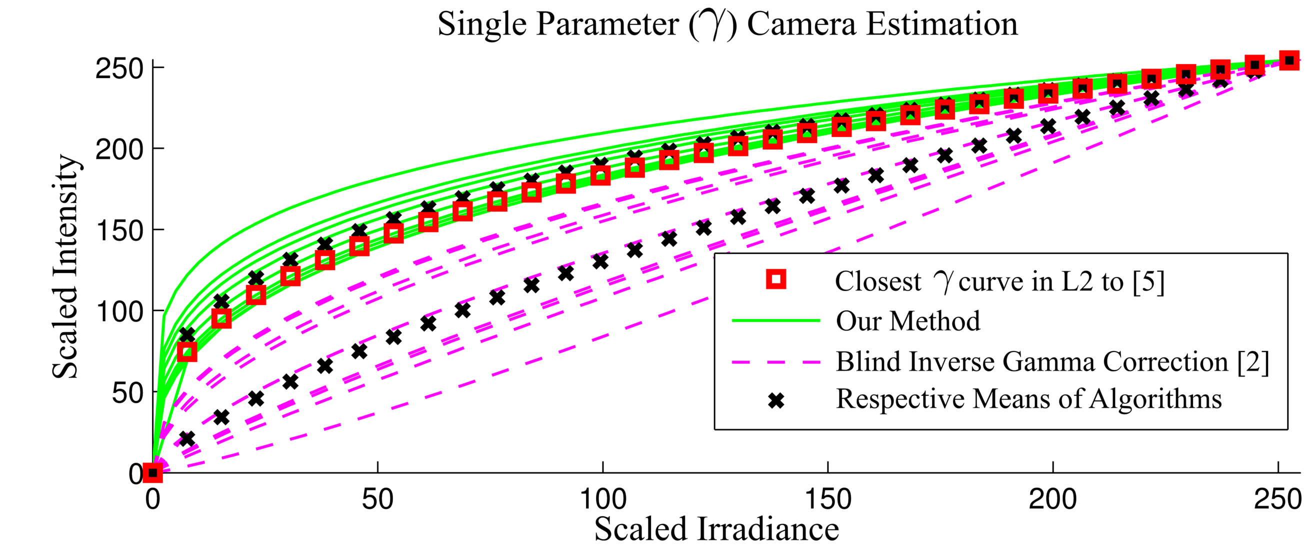
Nonlinear Camera Estimation

The approach enables an estimate of the radiometric response function from a single image by taking advantage of the similarity between the camera and texture models.



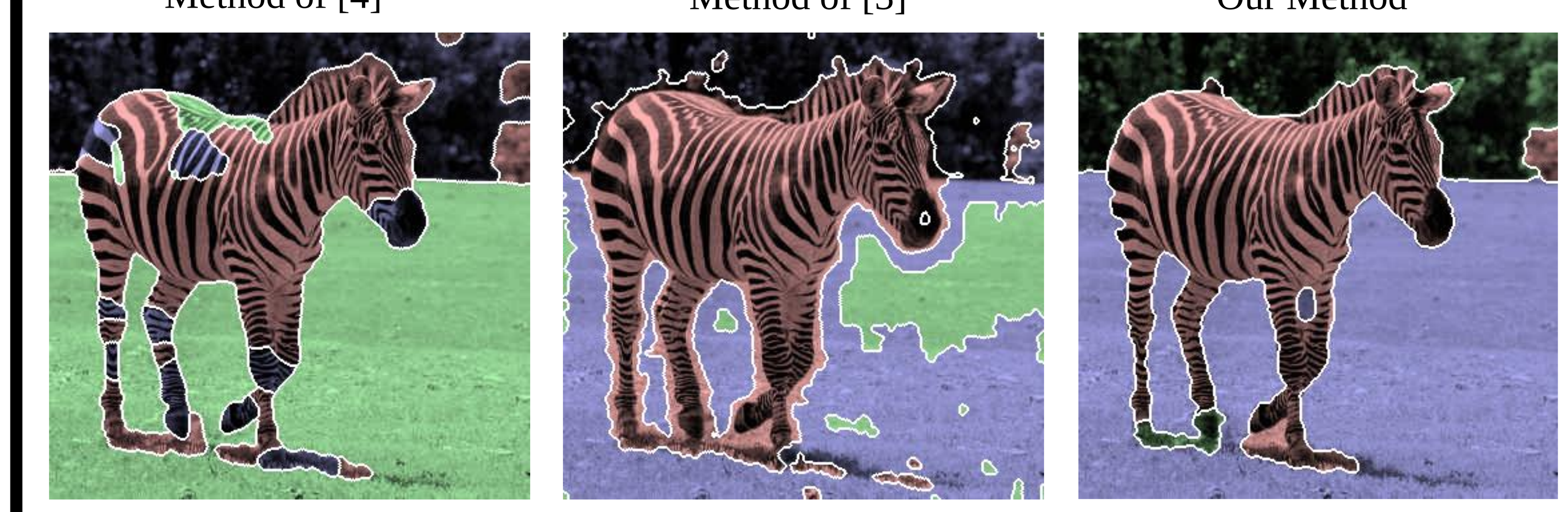
$\underline{\mathcal{R}}$ - Reflectance Image
$\underline{\mathcal{S}}$ - Shading Image
$\underline{\mathcal{I}}$ - Irradiance Image
$\underline{x}$ - Original Image
$\underline{g}$ - Gain Field
$\underline{b}$ - Bias Field

We took photographs of the same scene with multiple exposures and calibrated our camera using [5]. We then took a set of photographs and estimated the radiometric response using our method and the method of [2].



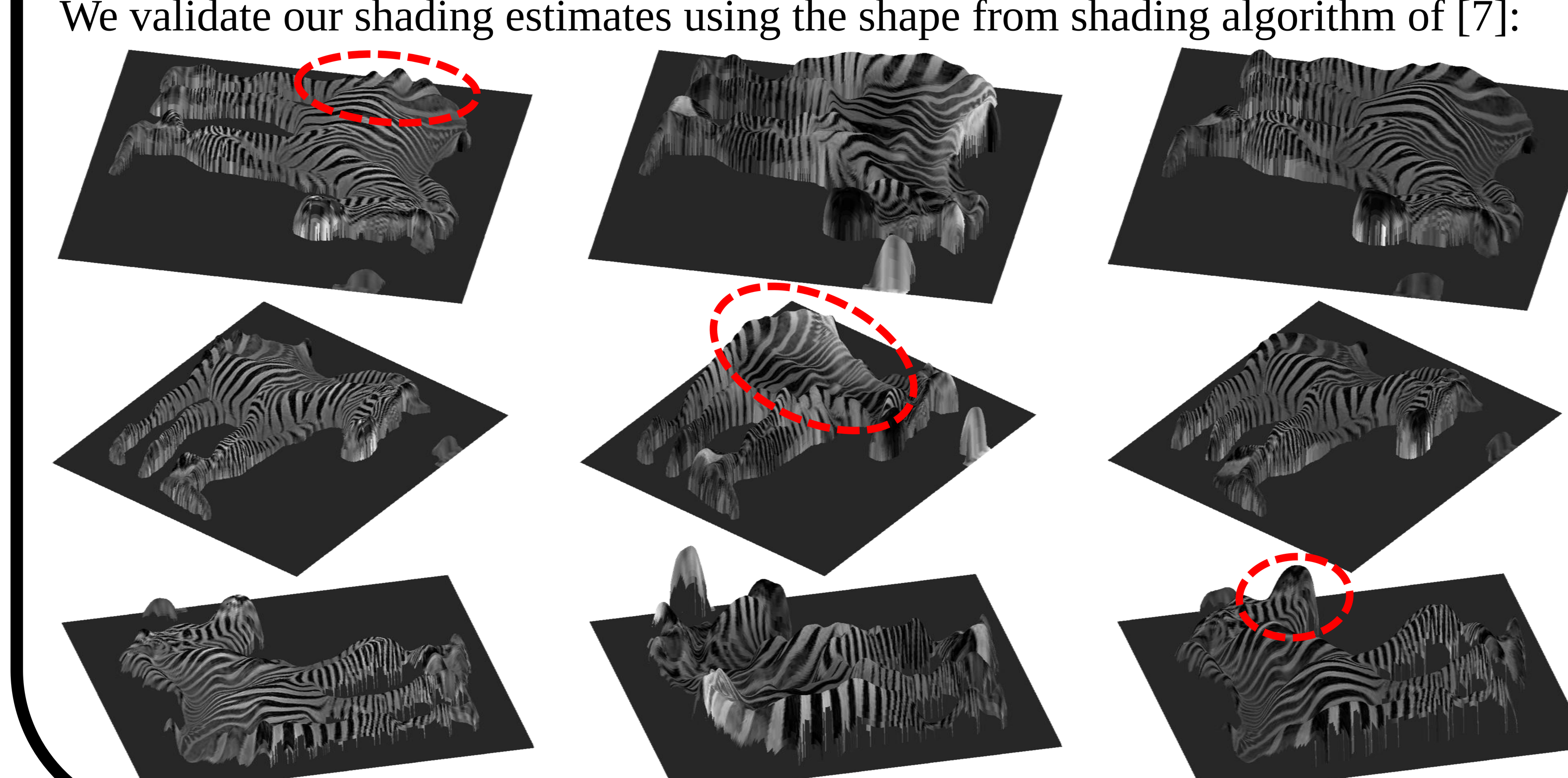
Shape from Shading

Once the nonlinear camera model has been estimated with our model, we are able to estimate a shading image. We first segment the image:



We then estimate the γ curve. Giving the methods of [4] and [3] the benefit of our segmentation and our estimate of γ, we estimate the reflectance and shading:

We validate our shading estimates using the shape from shading algorithm of [7]:



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