Harmonic Variance: A Novel Measure for In-focus Segmentation

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Detecting in-focus regions in a low depth-of-field (DoF) image has important applications in scene understanding, object-based coding, image quality assessment and depth estimation because such regions may indicate semantically meaningful objects. Most early approaches consider image sharpness as an image in-focus metric and attempt to measure in-focus directly from high-frequency components, e.g. edges [2] and patch variances [1]. However, in-focus edges with low intensity magnitudes and defocus edges with high intensity magnitudes may give similar responses. Thus, recent work formulates in-focus detection either as a learning task [5] or an optimization problem [7].

Here, we introduce an efficient in-focus measure to estimate the degree of in-focus within an image region and a graph segmentation based regularization method to accurately align the feature responses on the underlying image structure.

A harmonic mean of variances, which we call as *harmonic variance*, is computed from the statistical properties of the given image in its bandpass filtered versions. To find the bandpass responses, we apply the 2D discrete cosine transform (DCT) on image patches, e.g. in 8×8 windows, with a fixed number of bands $M = 64$. These DCT transform responses are bandpass filtered individually and then aggregated into the bandpass filtered image I_m for the DCT channel m.

Note that, even if most of the variances σ_m^2 of a defocus region may have small values, one large variance estimate in a low-frequency channel, which is quite common for textured yet blurry regions, could still make the arithmetic mean of the variances larger than that of in-focus regions, causing the defocus region to be falsely considered as in-focus. A competent in-focus measure should not be sensitive to such outliers. For positive data sets containing at least one pair of unequal values, the harmonic mean is always the smallest of the three means, while the arithmetic mean is the greatest of the three and the geometric mean is in between.

Thus, we use the harmonic mean instead of other possible first order statistics in order to combine the variances σ_m^2 of different bands. For a given patch centered at $\mathbf{x}$, we define the in-focus measure as the harmonic mean of the variances $\sigma_m^2(\mathbf{x})$

$$h(\mathbf{x}) = \left[\frac{1}{M-1} \sum_{m=1}^{M-1} \frac{1}{\sigma_m^2(\mathbf{x})} \right]^{-1} \tag{1}$$

omitting the variance of the zero-frequency channel σ_0^2. This in-focus measure is also closely related to the noise analysis of natural images [6] by a factor α as:

$$\sigma_\eta^2(\mathbf{x}) = \alpha(\mathbf{x}) \cdot h(\mathbf{x}) \, , \tag{2}$$

where σ_η^2 is the image noise variance and

$$\alpha(\mathbf{x}) = \frac{\sqrt{\kappa(\mathbf{x})} - \frac{1}{M-1}\sum_m \sqrt{\kappa_m(\mathbf{x})}}{\sqrt{\kappa(\mathbf{x})}} \, , \tag{3}$$

where κ and κ_m are the kurtosis values of the original image I and bandpass filtered image I_m. In other words, for an in-focus image, the harmonic mean can be used to determine local image noise variances.

We incorporate the harmonic variance measure within a robust segmentation framework based on a graph Laplacian spectrum constraint [4] to segment in-focus regions in low DoF images.

We compute a graph Laplacian matrix L [3] from the image I. The graph Laplacian spectrum constraint $Lf = 0$ enforces the image structure on the prior information, that is the harmonic variance results, in the data fidelity term $\|f-h\|^2$. With this constraint, the optimal f lies in the null-space of L. In other words, f is constant within each connected component of the corresponding graph G. Therefore, we define the in-focus segmentation as a least-squares constrained optimization problem as

$$\min_f \|f-h\|^2 \quad \text{s.t.} \quad Lf = 0. \tag{4}$$

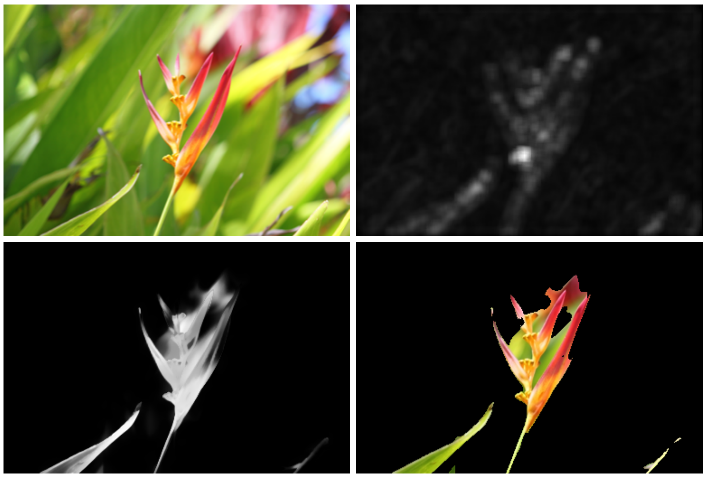

Figure 1: Top-row: original image and its harmonic variance features h. Bottom-row: the optimized in-focus likelihood scores f of h and the final segmentation. Unlike the conventional features, the harmonic variance is an accurate indicator of in-focus regions (please, see the full paper for comparisons). In addition, our method fits the harmonic score responses to the underlying image structure.

The residual $\delta(\mathbf{x}) = |f-h|$ has many spatially continuous outliers. The least-squares fidelity team with equal weights can distort the final estimate in case of outliers. We adapt a robust functional instead of the least-squares

$$\min_f \rho(f-h) + \beta\|Lf\|^2 \, , \tag{5}$$

where ρ is the robust function. We use the Huber function

$$\rho(\mathbf{x}) = \begin{cases} 1 & \text{if } \delta(\mathbf{x}) < \varepsilon \\ \varepsilon/\delta(\mathbf{x}) & \text{if } \delta(\mathbf{x}) \geq \varepsilon \end{cases} \tag{6}$$

for the reason that it is a parabola in the vicinity of 0 and increases linearly when δ is large. Thus, the effects of large outliers can be eliminated significantly. When written in a matrix form, the data fidelity term can be simplified as $\|W(f-h)\|^2$ where W represents the Huber weight function. As a result, the problem Eq.(5) can be solved efficiently in an iterative least-squares approach. At each iteration, the optimal f is updated as

$$f = (\beta L^\top L + W)^{-1} W h \, . \tag{7}$$

In conclusion, the effectiveness of this novel harmonic variance measure coupled with the image structure alignment capability of the graph Laplacian spectrum based robust optimization framework generates highly accurate segmentation results of in-focus regions in low DoF images.

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