Abstract

The Laplacian pyramid is ubiquitous for decomposing images into multiple scales and is widely used for image analysis. However, because it is constructed with spatially invariant Gaussian kernels, the Laplacian pyramid is widely believed to be ill-suited for representing edges, as well as for edge-aware operations such as edge-preserving smoothing and tone mapping. To tackle these tasks, a wealth of alternative techniques and representations have been proposed, e.g., anisotropic diffusion, neighborhood filtering, and specialized wavelet bases. While these methods have demonstrated successful results, they come at the price of additional complexity, often accompanied by higher computational cost or the need to post-process the generated results. In this paper, we show state-of-the-art edge-aware processing using standard Laplacian pyramids. We characterize edges with a simple threshold on pixel values that allows us to differentiate large-scale edges from small-scale details. Building upon this result, we propose a set of image filters to achieve edge-preserving smoothing, detail enhancement, tone mapping, and inverse tone mapping. The advantage of our approach is its simplicity and flexibility, relying only on simple point-wise nonlinearities and small Gaussian convolutions; no optimization or post-processing is required. As we demonstrate, our method produces consistently high-quality results, without degrading edges or introducing halos.

Keywords: image pyramids, edge-aware image processing

1 Introduction

Laplacian pyramids have been used to analyze images at multiple scales for a broad range of applications such as compression [Burt and Adelson 1983], texture synthesis [Heeger and Bergen 1995], and harmonization [Sunkavalli et al. 2010]. However, these pyramids are commonly regarded as a poor choice for applications in which image edges play an important role, e.g., edge-preserving smoothing or tone mapping. The isotropic, spatially invariant, smooth Gaussian kernels on which the pyramids are built are considered almost antithetical to edge discontinuities, which are precisely located and anisotropic by nature. Further, the decimation of the levels, i.e., the successive reduction by factor 2 of the resolution, is often criticized for introducing aliasing artifacts, leading some researchers, e.g., Li et al. [2005], to recommend its omission. These arguments are often cited as a motivation for more sophisticated schemes such as anisotropic diffusion [Perona and Malik 1990; Aubert and Kornprobst 2002], neighborhood filters [Tomasi and Manduchi 1998; Kass and Solomon 2010], edge-preserving optimization [Bhat et al. 2010; Farbman et al. 2008], and edge-aware wavelets [Fattal 2009].

While Laplacian pyramids can be implemented using simple image resizing routines, other methods rely on more sophisticated techniques. For instance, the bilateral filter relies on a spatially varying kernel [Tomasi and Manduchi 1998], optimization-based methods, such as [Fattal et al. 2002; Farbman et al. 2008; Subr et al. 2009; Bhat et al. 2010], minimize a spatially inhomogeneous energy, and other approaches build dedicated basis functions for each new image, e.g., [Szeliski 2006; Fattal 2009; Fattal et al. 2009]. This additional level of sophistication is also often associated with practical shortcomings. The parameters of anisotropic diffusion are difficult to set because of the iterative nature of the process, neighborhood filters tend to over-sharpen edges [Buades et al. 2006], and methods based on optimization do not scale well due to the algorithmic complexity of the solvers. While some of these shortcomings can be alleviated in post-processing, e.g., bilateral filtered edges can be smoothed [Durand and Dorsey 2002; Bae et al. 2006; Kass and Solomon 2010], this induces additional computation and parameter setting, and a method producing good results directly is preferable.
In this paper, we demonstrate that state-of-the-art edge-aware filters can be achieved with standard Laplacian pyramids. We formulate our approach as the construction of the Laplacian pyramid of the filtered output. For each output pyramid coefficient, we render a filtered version of the full-resolution image, processed to have the desired properties according to the corresponding local image value at the same scale, build a new Laplacian pyramid from the filtered image, and then copy the corresponding coefficient to the output pyramid. The advantage of this approach is that while it may be nontrivial to produce an image with the desired property everywhere, it is often easier to obtain the property locally. For instance, global detail enhancement typically requires a nonlinear image decomposition, e.g., [Fattal et al. 2007; Farbman et al. 2008; Subr et al. 2009], but enhancing details in the vicinity of a pixel can be done with a simple S-shaped contrast curve centered on the pixel intensity. This local transformation only achieves the desired effect in the neighborhood of a pixel, but is sufficient to estimate the fine-scale Laplacian coefficient of the output. We repeat this process for each coefficient independently and collapse the pyramid to produce the final output.

We motivate this approach by analyzing its effect on step edges and was previously thought impossible. We propose an algorithm show that edges can be differentiated from small-scale details with the final output. Scale Laplacian coefficient of the output. We repeat this process for intensity. This local transformation only achieves the desired effect in the neighborhood of a pixel, but is sufficient to estimate the fine-scale Laplacian coefficient of the output. We repeat this process for every pixel, and then copy the corresponding coefficient to the filtered output. For each output pyramid coefficient, we render an image in an edge-preserving way, and only a few techniques can be indeed obtained using only the Laplacian pyramid, which was previously thought impossible.

Contributions The main contribution of this work is a flexible approach to achieve edge-aware image processing through simple point-wise manipulation of Laplacian pyramids. Our approach builds upon a new understanding of how image edges are represented in Laplacian pyramids and how to manipulate them in a local fashion. Based on this, we design a set of edge-aware filters that produce high-quality halo-free results.

2 Related Work

Edge-aware Image Processing Edge-aware image manipulation has already received a great deal of attention and we refer to books and surveys for an in-depth presentation [Aubert and Kornprobst 2002; Kimmel 2003; Paris et al. 2009]. Recently, several methods have demonstrated satisfying results with good performance, e.g., [Chen et al. 2007; Farbman et al. 2008; Fattal 2009; Subr et al. 2009; Criminisi et al. 2010; He et al. 2010; Kass and Solomon 2010]. Our practical contribution is to provide filters that consistently achieve results at least as good, have easy-to-set parameters, can be implemented with only basic image resizing routines, are non-iterative, and do not rely on optimization or post-processing. In particular, unlike gradient-domain methods, e.g., [Fattal et al. 2002], we do not need to solve the Poisson equation which may introduce artifacts with non-integrable gradient fields. From a conceptual standpoint, our approach is based on image pyramids and is inherently multiscale, which differentiates it from methods that are expressed as a two-scale decomposition, e.g., [Chen et al. 2007; Subr et al. 2009; He et al. 2010].

Pyramid-based Edge-aware Filtering As described earlier, pyramids are not the typical representation of choice for filtering an image in an edge-preserving way, and only a few techniques along these lines have been proposed. A first approach is to directly rescale the coefficients of a Laplacian pyramid, however, this typically produces halos [Li et al. 2005]. While halos may be tolerable in the context of medical imaging, e.g., [Vuylsteke and Schoeters; Dippel et al. 2002], they are unacceptable in photography. Fattal et al. [2002] avoid halos by using a Gaussian pyramid to compute scaling factors applied to the image gradients. They reconstruct the final image by solving the Poisson equation. In comparison, our approach directly manipulates the Laplacian pyramid of the image and does not require global optimization. Fattal et al. [2007] use a multi-scale image decomposition to combine several images for detail enhancement. Their decomposition is based on repeated applications of the bilateral filter. Their approach is akin to building a Laplacian pyramid but without decimating the levels and with a spatially varying kernel instead of a Gaussian kernel. However, their study is significantly different from ours because it focuses on multi-image combination and speed. In a similar spirit, Farbman et al. [2008] compute a multi-scale edge-preserving decomposition with a least-squares scheme instead of bilateral filtering. This work also differs from ours since its main concern is the definition and application of a new optimization-based filter. In the context of tone mapping, Mantiuk et al. [2006] model human perception with a Gaussian pyramid. The final image is the result of an optimization process, which departs from our goal of working only with pyramids.

Fattal [2009] describes wavelet bases that are specific to each image. He takes edges explicitly into account to define the basis functions, thereby reducing the correlation between pyramid levels. From a conceptual point of view, our work and Fattal’s are complementary. Whereas he designed pyramids in which edges do not generate correlated coefficients, we seek to better understand this correlation to preserve it during filtering.

Li et al. [2005] demonstrate a tone-mapping operator based on a generic set of spatially-invariant wavelets, countering the popular belief that such wavelets are not appropriate for edge-aware processing. Their method relies on a corrective scheme to preserve the spatial and intra-scale correlation between coefficients, and they also advocate computing each level of the pyramid at full resolution to prevent aliasing. However, when applied to Laplacian pyramids, strong corrections are required to avoid halos, which prevents a large increase of the local contrast. In comparison, in this work, we show that Laplacian pyramids can produce a wide range of edge-aware effects, including extreme detail amplification, without introducing halos.

Gaussian pyramids are closely related to the concept of Gaussian scale-space defined by filtering an image with a series of Gaussian kernels of increasing size. While these approaches are also concerned with the correlation between scales created by edges, they are used mostly for purposes of analysis, e.g., [Witkin 1983; Witkin et al. 1987].

Background on Gaussian and Laplacian Pyramids Our approach is based on standard image pyramids, whose construction we summarize briefly. For more detail, see [Burt and Adelson 1983]. Given an image \( I \), its Gaussian pyramid is a set of images \( \{ G_k \} \) called levels, representing progressively lower resolution versions of the image, in which high-frequency details progressively disappear. In the Gaussian pyramid, the bottom-most level is the original image, \( G_0 = I \), and \( G_{i+1} = \text{downsample}(G_i) \) is a low-pass version of \( G_i \) with half the width and height. The filtering and decimation process is iterated \( n \) times, typically until the level \( G_n \) has only a few pixels. The Laplacian pyramid is a closely related construct, whose levels \( \{ L_i \} \) represent details at different spatial scales, decomposing the image into roughly separate fre-
quency bands. Levels of the Laplacian pyramid are defined by the
details that distinguish successive levels of the Gaussian pyramid,
\( L_\ell = G_\ell \times \text{upsample}(G_{\ell+1}) \), where \text{upsample}() is an operator that
doubles the image size in each dimension using a smooth kernel.
The top-most level of the Laplacian pyramid, also called the resid-
ual, is defined as \( L_\ell = G_\ell \) and corresponds to a tiny version of the
image. A Laplacian pyramid can be collapsed to reconstruct the
original image by recursively applying \( G_\ell = L_\ell + \text{upsample}(G_{\ell+1}) \)
until \( G_0 = I \) is recovered.

### 3 Dealing with Edges in Laplacian Pyramids

The goal of edge-aware processing is to modify an input signal
\( I \) to create an output \( I' \), such that the large discontinuities of \( I \), i.e., its edges, remain in place, and such that their profiles retain
the same overall shape. For example, the amplitude of significant
edges may be increased or reduced, but the edge transitions should
not become smoother or sharper. The ability to process images
in this edge-aware fashion is particularly important for techniques
that manipulate the image in a spatially-varying way, such as im-
age enhancement or tone mapping. Failure to account for edges in
these applications leads to distracting visual artifacts such as halos,
shifted edges, or reversals of gradients. In the following discussion,
for the sake of illustration, we focus on the case where we seek to
reduce the edge amplitude—the argument when increasing the edge
amplitude is symmetric.

In this work, we characterize edges by the magnitude of the cor-
responding discontinuity in a color space that depends on the ap-
plication; we assume that variations due to edges are larger than
those produced by texture. This model is similar to many exist-
ing edge-aware filtering techniques, e.g., [Aubert and Kornprobst
2002; Paris et al. 2009]; we will discuss later the influence that
this assumption has on our results. Because of this difference in
magnitude, Laplacian coefficients representing an edge also tend to
be larger than those due to texture. A naive approach to decrease
the edge amplitude while preserving the texture is to truncate these
large coefficients. While this creates an edge of smaller amplitude,
it ignores the actual “shape” of these large coefficients and assigns
the same lower value to all of them. This produces an overly smooth
edge, as shown in Figure 2.

Intuitively, a better solution is to scale down the coefficients that
correspond to edges, to preserve their profile, and keep the other
coefficients unchanged, so that only the edges are altered. However,
it is unclear how to separate these two kinds of coefficients since
details with different profiles generate different coefficients across
scales. On the other hand, according to our model, edges are easy
to identify in image space; a threshold on color differences suffices
to differentiate edges from variations due to texture. This is a key
aspect of our approach: we generate new pyramid coefficients by
working primarily on the input image itself, rather than altering the
pyramid coefficients directly.

The overall design of our algorithm derives from this insight: we
build an approximation of the desired output image specific to each
pyramid coefficient. This is a major difference with the existing
literature. Whereas previous techniques are formulated in terms of
optimization, e.g., [Farbman et al. 2008], PDEs, e.g., [Perona and
Malik 1990], or local averaging, e.g., [Tomasi and Manduchi 1998],
we express our filter through the computation of these local image
approximations together with standard image pyramid manipula-
tions. In practice, we use locally-processed versions of the input
to recompute values for each pyramid coefficient, and combine all
of these new coefficient values into the final result. For each coeff-
icient at location \((x,y,\ell)\) and level \(\ell\), we first determine the region
in the input image on which this coefficient depends. To reduce

the amplitude of edges, for example, we clamp all the pixels values
in that region so that the difference to the average value does not
exceed a user-provided threshold. This processed image has the
desired property that edges are now limited in amplitude, to at most
twice the threshold. This also has the side effect of flattening the de-
tails across the edge. As we discuss below, these details are not lost,
they are actually captured by pyramid coefficients centered on the
other side of the edge as illustrated in Figure 3. Then, we compute
the Laplacian pyramid of this processed image to create coefficients
that capture this property. In particular, this gives us the value of the
coefficient \((x,y,\ell)\) that we seek. Another way of interpreting
our method is that we locally filter the image, e.g., through a local
contrast decrease, and then determine the corresponding coefficient
in the Laplacian pyramid. We repeat this process, such that each
coefficient in the pyramid is computed.

**Detail Preservation** As mentioned earlier, a reasonable concern
at this point is that the clamped image has lost details in the thresh-
olded regions, which in turn could induce a loss in the final output.

- **Figure 2:** Range compression applied to a step edge with fine de-
tails (a). The different versions of the edge are offset vertically so
that their profiles are clearly visible. Truncating the Laplacian co-
efficients smooths the edge (red), an issue which Li et al. [2005]
have identified as a source of artifacts in tone mapping. In compar-
ison, our approach (blue) preserves the edge sharpness and very
closely reproduces the desired result (black). Observing the shape
of the first two levels (b,c) shows that clipping the coefficients sig-
ificantly alters the shape of the signal (red vs. orange). The truncated
coefficients form wider lobes whereas our approach produces pro-
files nearly identical to the input (blue vs. orange).

- **Figure 3:** Simple view of our range compression approach, which is
based on thresholding and local processing. For a step-like signal
similar to the one in Figure 2, our method effectively builds two
Laplacian pyramids, corresponding to clipping the input based on
the signal value to the left and right of the step edge, then merging
their coefficients as indicated by the color coding.
However, the loss of details does not transfer to our final result. Intuitively, the clamped details are on “the other side of the edge” and are represented by other coefficients. Applying this scheme to all pyramid coefficients accurately represents the texture on each side of the edge, while capturing the reduction in edge amplitude (Fig. 3). Further, clamping affects only half of the edge and, by combining coefficients on “both sides of the edge”, our approach reconstructs an edge profile that closely resembles the input image, i.e., the output profiles do not suffer from over-smoothing. Examining the pyramid coefficients reveals that our scheme fulfills our initial objective, that is, that the edge coefficients are scaled down while the other coefficients representing the texture are preserved (Fig. 2).

4 Local Laplacian Filtering

We now formalize the intuition gained in the previous section and introduce Local Laplacian Filtering, our new method for edge-aware image processing based on the Laplacian pyramid. A visual overview is given in Figure 4 and the pseudo-code is provided in Algorithm 1.

In Local Laplacian Filtering an input image is processed by constructing the Laplacian pyramid \( \{L'_j[I]\} \) of the output, one coefficient at a time. For each coefficient \((x, y, \ell)\), we generate an intermediate image \( I \) by applying a point-wise monotonic remapping function \( r_{\ell,\sigma}(\cdot) \) to the original full-resolution image. This remapping function, whose design we discuss later, depends on the local image value from the Gaussian pyramid \( g = G_{\ell}(x, y) \) and the user parameter \( \sigma \) which is used to distinguish edges from details. We compute the pyramid for the intermediate image \( \{L[I]\} \) and copy the corresponding coefficient to the output \( \{L'_j[I]\} \). After all coefficients of the output pyramid have been computed, we collapse the output pyramid to get the final result.

A direct implementation of this algorithm yields a complexity in \( \mathcal{O}(N^2) \) with \( N \) being the number of pixels in the image, since each coefficient entails the construction of another pyramid with \( \mathcal{O}(N) \) pixels. However, this cost can be reduced in a straightforward way by processing only the sub-pyramid needed to evaluate \( L_{\ell}[I](x, y) \), illustrated in Figure 4. The base of this sub-pyramid lies within a \( K \times K \) sub-region \( R \) of the input image \( I \), where \( K = \mathcal{O}(2^\ell) \); for Laplacian pyramids built using a standard 5-tap interpolation filter, it can be shown that \( K = 3(2^{\ell+2} - 1) \). Put together with the fact that level \( \ell \) contains \( \mathcal{O}(N/2^\ell) \) coefficients, each level requires the manipulation of \( \mathcal{O}(N) \) coefficients in total. Since there are \( \mathcal{O}(\log N) \) levels in the pyramid, the overall complexity of our algorithm is \( \mathcal{O}(N \log N) \). Later we will see that some applications only require a fixed number of levels to be processed or limit the depth of the sub-pyramids to a fixed value, reducing the complexity of our algorithm further.

Remapping Function for Gray-scale Images We assume the user has provided a parameter \( \sigma \) such that intensity variations smaller than \( \sigma \) should be considered fine-scale details and larger variations are edges. As a center point for this function we use \( g = G_{\ell}(x, y) \), which represents the image intensity at the location and scale where we compute the output pyramid coefficient. Intuitively, pixels closer than \( \sigma \) should be processed as details and those farther than \( \sigma \) away should be processed as edges. We differentiate their treatment by defining two functions \( r_d \) and \( r_e \), such that \( r(i) = r_d(i) \) if \(|i - g| < \sigma \) and \( r(i) = r_e(i) \) otherwise. Since we require \( r \) to be monotonically increasing, \( r_d \) and \( r_e \) must have this property as well. Furthermore, to avoid the creation of spurious discontinuities, we constrain \( r_d \) and \( r_e \) to be continuous by requiring that \( r_d(g + \sigma) = r_e(g + \sigma) \).

The function \( r_d \) modifies the fine-scale details by altering the oscillations around the value of \( g \). In our applications we process positive and negative details symmetrically, letting us write:

\[
\begin{align*}
    r_d(i, g, \sigma) &= g + \mathrm{sign}(i - g) \cdot f_d(|i - g|/\sigma) \quad (1) \\
    r_e(i, g, \sigma) &= g + \mathrm{sign}(i - g) \cdot f_e(|i - g|/\sigma) + \sigma \quad (2)
\end{align*}
\]

where \( f_d \) is a smooth function mapping from \([0, 1]\) to \([0, 1]\) that controls how details are modified. The advantage of this formulation is that it depends only on the amplitude of the detail \(|i - g|\) relative to the parameter \( \sigma \), i.e., \(|i - g|/\sigma = 1 \) corresponds to a detail of maximum amplitude according to the user-defined parameter. Analogously, \( r_e \) is a function that modifies the amplitude of edges that we again formulate in a symmetric way:

\[
\begin{align*}
    r_e(i, g, \sigma) &= g + \mathrm{sign}(i - g) \cdot (f_e(|i - g|/\sigma) + \sigma) \\
    \end{align*}
\]

where \( f_e \) is a smooth non-negative function defined over \([0, \infty)\). In this formulation, \( r_e \) depends only on the amplitude above the user threshold \( \sigma \), i.e., \(|i - g| > \sigma \). The function \( f_e \) controls how the edge amplitude is modified since an edge of amplitude \( \sigma + a \) becomes an edge with amplitude \( \sigma + f_e(a) \). For our previous 1D range compression example, clipping edges corresponds to \( f_e = 0 \), which limits the amplitude of all edges to \( \sigma \). Useful specific choices for \( r_d \) and \( r_e \) are described in the next section and are illustrated in Figure 5.

Algorithm 1 \( \mathcal{O}(N \log N) \) version of Local Laplacian Filtering

**input:** image \( I \), parameter \( \sigma \), remapping function \( r \)

**output:** image \( I' \)

1. compute input Gaussian pyramid \( \{G[I]\} \)
2. for all coefficients at position \((x, y)\) and level \( \ell \) do
3.   \( g \leftarrow G_{\ell}(x, y) \)
4.   determine sub-region \( R \) of \( I \) needed to evaluate \( L_{\ell}(x, y) \)
5.   create temporary buffer \( R \) of the same size
6.   for all pixels \((u, v)\) of \( R \) do
7.     apply remapping function: \( R(u, v) \leftarrow r(R(u, v), g, \sigma) \)
8.   end for
9.   compute sub-pyramid \( \{L[R]\} \)
10.  update output pyramid: \( L_{\ell}[I'](x, y) \leftarrow L_{\ell}[R](x, y) \)
11. end for
12. collapse output pyramid: \( I' \leftarrow \text{collapse}(\{L'[I]\}) \)

Our algorithm considers the pyramid coefficients one by one (Step 2). Each of them is computed using the pixels from the finest resolution (Step 4) by applying the remapping function to them (Step 7) and building a Laplacian pyramid of the remapped data (Step 9). We copy the relevant coefficient into the output pyramid (Step 10) and once all the coefficients have been computed, we collapse pyramid the get the final result (Step 12).
5 Applications and Results

We now demonstrate how to realize practical image processing applications using our approach and discuss implementation details. First we address edge-preserving smoothing and detail enhancement, followed by tone mapping and related tools. We validate our method with images used previously in the literature [Fattal et al. 2002; Durand and Dorsey 2002; Paris et al. 2009; Farbman et al. 2008; Fattal 2009] and demonstrate that our method produces artifact-free results.

The advantage of the functional forms defined in Equations 1 and 2 is that they ensure that \( r \) is continuous and increasing, and the design of a specific filter boils down to defining the two point-wise functions \( f_d \) and \( f_e \) that each have clear roles: \( f_d \) controls the amplification or attenuation of details while \( f_e \) controls the amplification or attenuation of edges.

Extension to Color Images. To handle color, it is possible to treat only the luminance channel and reintroduce chrominance after image processing (Sec. 5.3). However, our approach extends naturally to color images as well, letting us deal directly with 3D vectors representing, e.g., the RGB or CIE-Lab channels. Algorithm 1 still applies, and we need only to update \( r_d \) and \( r_e \), using bold typeface to indicate vectors:

\[
\begin{align*}
    r_d(i, g, \sigma) &= g + \text{unit}(i - g) \cdot \sigma f_d(\|i - g\| / \sigma) \quad (3a) \\
    r_e(i, g, \sigma) &= g + \text{unit}(i - g) \cdot \left[f_e(\|i - g\| - \sigma) + \sigma\right] \quad (3b)
\end{align*}
\]

with \( \text{unit}(v) = v / \|v\| \) if \( v \neq 0 \) and 0 otherwise. These equations define details as colors within a ball of radius \( \sigma \) centered at \( g \) and edges as the colors outside it. They also do not change the roles of \( f_d \) and \( f_e \), letting the same 1D functions that modify detail and edges in the gray-scale case be applied to generate similar effects in color. For images whose color channels are all equal, these formulas reduce to the gray-scale formulas of Eq. 1 and 2.

5.1 Implementation

We use the pyramids defined by Burt and Adelson [1983], based on \( 5 \times 5 \) kernels. On a 2.26GHz Intel Xeon CPU, we process a one-megapixel image in about a minute using a single thread. This can be halved by limiting the depth of the intermediate pyramid to at most 5 levels, by applying the remapping to level \( \max(0, \ell - 3) \) rather than always starting at the full-resolution image. This amounts to applying the remapping to a downsampled version of the image when processing coarse pyramid levels. The resulting images are visually indistinguishable from the full-pyramid process with a PSNR on the order of 30 to 40dB. While this performance is slower than previous work, our algorithm is highly data parallel and can easily exploit a multi-core architecture. Using OpenMP, we obtain a \( 8 \times \) speed-up on an 8-core machine, bringing the running time down to 4 seconds.
5.2 Detail Manipulation

To modify the details of an image, we define an S-shaped point-wise function as is classically used for the local manipulation of contrast. For this purpose, we use a power curve \( f_\alpha(\Delta) = \Delta^\alpha \), where \( \alpha > 0 \) is a user-defined parameter. Values larger than 1 smooth the details out, while values smaller than 1 increase their contrast (Figs. 5 and 6). To restrict our attention to the details of an image, we set the edge-modifying function to the identity \( f_\tau \) where \( \tau \) is less than 1% \( \Delta \leq \tau \). Figure 8: Filtering only the luminance (b) preserves the original contrast. For this purpose, we set the edge-modifying function to the identity \( f_\tau \) where \( \tau \) is less than 1% \( \Delta \leq \tau \).

Reducing Noise Amplification As in other techniques for texture enhancement, increasing the contrast of the details may make noise and artifacts from lossy image compression more visible. We mitigate this issue by limiting the smallest \( \Delta \) amplified. In our implementation, when \( \alpha < 1 \), we compute \( f_\alpha(\Delta) = \tau \Delta + (1 - \tau) \Delta \) where \( \tau \) is a smooth step function equal to 0 if \( \Delta \) is less than 1% of the maximum intensity, 1 if it is more than 2%, with a smooth transition in between. All the results in this paper and supplemental material are computed with this function.

5.3 Tone Manipulation

Our approach can also be used for reducing the intensity range of a HDR image, according to the standard tone mapping strategy of compressing the large-scale variations while preserving (or enhancing) the details [Tumblin and Turk 1999]. In our framework, we manipulate large-scale variations by defining a point-wise function modifying the edge amplitude, \( f_\beta(a) = \beta a \), where \( \beta \geq 0 \) is a user-defined parameter (Fig. 5).

In our implementation of tone manipulation we process the image intensity channel only and keep the color unchanged [Durand and Dorsey 2002]. We compute an intensity image \( I_i = \frac{1}{256}(20I_r + 40I_g + I_b) \) and color ratios \( \rho_r, \rho_g, \rho_b \) = \( \frac{1}{2}(I_r, I_g, I_b) \) where \( I_r, I_g, \) and \( I_b \) are the RGB channels. We apply our filter on the log intensities \( \log(I_i) \) [Tumblin and Turk 1999], using the natural logarithm. For tone mapping, we set our filter with \( \alpha \leq 1 \) so that details are preserved or enhanced, and \( \beta < 1 \) so that edges are compressed. This produces new values \( \log(I_i') \), which we must then map to the displayable range of \( [0, 1] \). We remap the result \( \log(I_i') \) by first offsetting its values to make its maximum 0, then scaling them so that they cover a user-defined range [Durand and Dorsey 2002; Li et al. 2005]. In our implementation, we estimate a robust maximum and minimum with the 99.5th and 0.5th percentiles, and we set the scale factor so that the output dynamic range is 1:1 for the linear intensities. Finally, we multiply the intensity by the color ratios \( \rho_r, \rho_g, \rho_b \) to obtain the output RGB channels, then gamma correct with an exponent of 1/2.2 for display. We found that fixing the output dynamic range makes it easy to achieve a consistent look but also constrains the system. As a result, the \( \sigma \) and \( \beta \) parameters have similar effects, both controlling the balance between local and global contrast in the rendered image (Fig. 9). From a practical standpoint, we advise keeping \( \sigma \) fixed and varying the slope \( \beta \) between 0, where the local contrast is responsible for most of the dynamic range, and 1, where the global contrast dominates. Unless otherwise specified, we use \( \sigma = \log(2.5) \), which gave consistently good results in our experiments. Since we work in the log domain, this value corresponds to a ratio between pixel intensities. It does not depend on the dynamic range of the scene, and assumes only that the input HDR image measures radiance up to scale.

Our tone mapping operator builds upon standard elements from previous work that could be substituted for others. For instance, one could instead use a sigmoid to remap the intensities to the display range [Reinhard et al. 2002] or use a different color management method, e.g., [Mantiuk et al. 2009]. Also, we did not apply any additional “beautifying curve” or increased saturation as is commonly done in photo editing software. Our approach produces a clean output image that can be post-processed in this way if desired.
stress-tested our operator by producing results with a low global contrast ($\beta = 0$) and high local details ($\alpha = 0.25$). In general, the results produced by our method did not exhibit any particular problems (Fig. 16). We compare exaggerated renditions of our method with Farbman et al. [2008] and Li et al. [2005]. Our method produces consistent results without halos, whereas the other methods either create halos or fail to exaggerate detail (Fig. 14).

One typical difficulty we encountered is that sometimes the sky interacts with other elements to form high-frequency textures that undesirably get amplified by our detail-enhancing filter (Figs. 8b and 12). Such “misinterpretation” is common to all low-level filters without semantic understanding of the scene, and typically requires user feedback to correct [Lischinski et al. 2006].

We also experimented with inverse tone mapping, using slope values $\beta$ larger than 1 to increase the dynamic range of a normal image. Since we operate on log intensities, roughly speaking the linear dynamic range gets exponentiated by $\beta$. Applying our tone-mapping operator on these range-expanded results gives images close to the originals, typically with a PSNR between 25 and 30dB for $\beta = 2.5$. This shows that our inverse tone mapping preserves the image content well. While a full-scale study on an HDR monitor is beyond the scope of our paper, we believe that our simple approach can complement other relevant techniques, e.g., Masia et al. [2009]. Sample HDR results are provided in supplemental material.

5.4 Discussion

While our method can fail in the presence of excessive noise or when extreme parameter settings are used (e.g., the lenna picture in supplemental material has a high level of noise), we found that our filters are very robust and behave well over a broad range of settings. Figure 15 shows a variety of parameters values applied to the same image and the results are consistently satisfying, high-quality, and halo-free; many more such examples are provided in supplemental material. While the goal of edge-aware processing can be ill-defined, the results that we obtain shows that our approach allows us to realize many edge-aware effects with intuitive parameters and a simple implementation. The current shortcoming of our approach is its running time. We can mitigate this issue thanks to the multi-scale nature of our algorithm, allowing us to generate quick previews that are faithful to the full resolution results (Fig. 13). Furthermore, the algorithm is highly parallelizable and should lend itself to a fast GPU implementation. Beyond these practical aspects, our main contribution is a better characterization of the multi-scale properties of images. Many problems related to photo editing are grounded in these properties of images and we believe that a better understanding can have benefits beyond the applications demonstrated in this paper.

6 Conclusion

Link to Recent Work We first presented this work at the ACM SIGGRAPH conference in 2011. The main difference with our original article is Section 3 that now focuses on qualitative properties of edges. A formal discussion of these properties can be found in [Paris et al. 2011]. Since then, we also extended this work with a fast algorithm that makes Local Laplacian Filters practical, an analysis that shows their relationship to the Bilateral Filter, an

Figure 10: The extreme contrast near the light bulb is particularly challenging. Images (a) and (b) are reproduced from [Fattal 2009]. The edge-aware wavelets suffer from aliasing and generate an irregular edge (b). In comparison, our approach (d) produces a clean edge. We set our method to approximately achieve the same level of details ($\sigma = \log(3.5)$, $\alpha = 0.5$, $\beta = 0$).

Figure 11: The bilateral filter sometimes over-sharpens edges, which can lead to artifacts (b). We used code provided by [Paris and Durand] and multiplied the detail layer by 2.5 to generate these results. Although such artifacts can be fixed in post-processing, this introduces more complexity to the system and requires new parameters. Our approach produces clean edges directly (d). We set our method to achieve approximately the same visual result ($\sigma = \log(2.5)$, $\alpha = 0.5$, $\beta = 0$).
application to the transfer of gradient histograms applied to photographic style transfer, and additional comparisons with existing techniques such as the Guided Filter [He et al. 2010]. These results are described in [Aubry et al. 2011].

Although Local Laplacian Filters can reduce image details, Xu et al. [2011; 2012] have shown that they do not fully remove them and have proposed filters that completely suppress details for applications such as cartoon rendering and mosaic texture removal. By addressing the extreme detail removal problem, this work is complementary to Local Laplacian Filters that perform well at extreme detail increase. Hadwiger et al. [2012] have introduced a dedicated data structure to process very large images efficiently and have demonstrated its application to Local Laplacian Filtering.

**Closing Note**  We have presented a new technique for edge-aware image processing based solely on the Laplacian pyramid. It is conceptually simple, allows for a wide range of edge-aware filters, and consistently produces artifact-free images. We demonstrate high-quality results over a large variety of images and parameter settings, confirming the method’s robustness. Our results open new perspectives on multi-scale image analysis and editing since Laplacian pyramids were previously considered as ill-suited for manipulating edges. Given the wide use of pyramids and the need for edge-aware processing, we believe our new insights can have a broad impact in the domain of image editing and its related applications.

**Acknowledgments**  We would like to thank Ted Adelson, Bill Freeman and Frédéric Durand for inspiring discussions and encouragement, Alan Erickson for the *Orion* image, and the anonymous reviewers for their constructive comments. This work was supported in part by an NSERC Postdoctoral Fellowship, the Quanta T-Party, NGA NEGI-1582-04-0004, MURI Grant N00014-06-1-0734, and gifts from Microsoft, Google and Adobe. We thank Farbman et al. and Li et al. for their help with comparisons.

**References**

Our approach is purely signal-based and its ignorance of scene semantics can lead to artifacts. For a large increase in local contrast (b), at a level similar to Figure 16, the sky gets locally darker behind clouds, because it forms a blue-white texture amplified by our filter. Our result for this example is good elsewhere, and this issue does not appear with a more classical rendition (a).

Our approach generates faithful previews when applied to a low-resolution version of an image ($\beta = 0, \sigma = \log(2.5)$).


Figure 15: Our filter to enhance and reduce details covers a large space of possible outputs without creating halos.

Figure 16: We stressed our approach by applying a strong range compression coupled with a large detail increase ($\alpha = 0.25$, $\beta = 0$, $\sigma = \log(2.5)$). The results are dominated by local contrast and are reminiscent of the popular, exaggerated “HDR look” but without the unsightly halos associated with it. In terms of image quality, our results remain artifact-free in most cases. We explore further parameter variations in the supplemental material.