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EDGE – PRESERVATION OF MULTISCALE IMAGES

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ABSTRACT

We propose a model for detail that captures oscillations and we use the local extrema of the input image to extract information about oscillations..We propose a simple algorithm for decomposing images into multiple scales. Currently used edge-preserving image decomposition techniques consider image detail to be of low contrast variation. They apply filters which extract features with increasing contrast as successive layers of detail. Thus they are unable to distinguish between high contrast, fine-scale features and edges of similar contrast that are to be preserved. We compare our results with existing edge-preserving image decomposition algorithms.

KEYWORDS: detail, oscillations, image decomposition.

1. INTRODUCTION

A lot of applications in digital image capture and processing technique require decomposition of an image into different scales. Recently scales are defined based on spatial scale definitions combined with the idea to differentiate strong edges. Existing approaches share a common idea of an edge– large gradients, or large value differences. This makes it challenging to capture fine details or textures that have fine spatial scale but high contrast. For example, in Figure 1(d), edges that are to be preserved are lower contrast than the oscillations to be smoothed. Extracting the white dots on the vase as detail requires aggressive smoothing of gradients. This may blur single edges that are to be preserved. There raises a challenge in defining fully multistage decompositions as the interplay between spatial and edge consideration leads to unexpected results. Here we are proposing a non-linear image decomposition technique that extracts fine-scale features, regardless of their contrast, as detail and yet preserves softer salient edges in the base layer. Our approach captures local image oscillations by considering local image extrema. Fine-scale texture is characterized by rapid oscillations between minima and maxima and the oscillation which are between extrema provide critical information that permit the distinction of individual edges from oscillations. We obtain a multiscale decomposition by recursively smoothing the image while also progressively coarsening the scale at which extrema are detected.

Figure 1: (a) allowing detail to be extracted based on spatial scale rather than contrast and preserves edges. (b) Boosting of fine scale features ;thus increasing contrasr(c) Boosting of coarse scale contrast ;suppressing fine features ;thus reducing contrast of the pattern and increasing the contrast of the vase with background. (d) Scanline plots

2. EXTREMA-BASED MULTISCALE DECOMPOSITION

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Based on local extrema, we introduce novel definitions for edges and detail that permit the distinction between highly contrasted texture and single edges. We then develop an edge-preserving smoothing algorithm that allows fine scale detail to be extracted regardless of contrast. We perform an edge-preserving multiscale decomposition by recursively applying the smoothing algorithm on the base layer where the decomposition corresponds to features at different spatial scales with salient edges being preserved. Finally we compare our approach with existing decompositions and demonstrate its effectiveness using applications.

	Definition of Detail	*Definition of Edge*	*Assumption*
Bilateral Filter	Low contrast variation	Large intensity difference	Texture is low-contrast
WLS Filter	Low contrast variation	Large gradient	Magnitude of gradient is larger at edges
BEMD	Fine-scale spatial oscillations	No notion of edge	Means of oscillations are smooth
Our Algorithm	Fine-scale spatial oscillations	High variance range values ofneighboring localextrema	Detail is in oscillations between localextrema

Figure 2: 3 techniques for image decomposition with existiing methode - Bilateral filtering , weighted least squares (WLS) filtering and bidimensional empirical mode decomposition (BEMD) .

The detail inherently captures repetitive variation of intensity,termed oscillations. The amplitudes of oscillations represent contrast while spatial-frequencies represents fineness in scale. Our goal is to smooth fine-scale oscillations, regardless of their amplitudes (see Fig 3). We extract the locally finest-scale oscillations as detail using a single smoothing operation, and by progressive smoothing we obtain a multiscale decomposition. We coarsen the scale at which extrema are detected by successive smoothing operations on the residual.

Morphological operations do not preserve shapewhile empirical decomposition does not preserve edges . We exploit this information to preserve both edges and shape. Our algorithm is based on two key observations:

- Detail, characterized by a large density of local extrema;
- salient edges , characterized by a large variation in their neighboring extremal values The two important benefits of using local extreme upon contrast are :
- We make no assumptins on the dynamic range of the input image or on its amplitudes.
- We obtain the local scale of oscillations independent of contrast.

Recursive removal of detail cause the degrees of coarseness in the multiscale decomposition to capture the inherent superimposed scales of oscillation in the input image.We describe our algorithm for an input grayscale image I and perform the decomposition on the luminance channel for color images. We denote image-space coordinates (x, y) with boldface letters. Thus I(p) is the intensity of the given grayscale image I at pixel p.

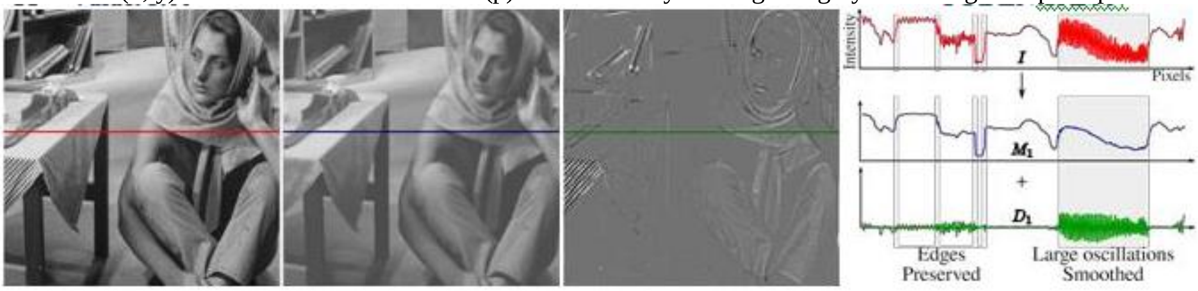

Figure 3: Input intensities (red) along a row,separation into detail (green) and mean (blue). Some oscillations are extracted as detail D1 , while single edges having lower amplitude are preserved in the smoothed mean M1.

A. Smoothing

We define detail as oscillations between local minima and maxima (see Fig 4).Detail is extracted by subtracting a smoothed image, that we call the mean, from the input. The smoothing algorithm detect oscillations at their finest scale, locally, using the local extrema, We construct two extremal envelopes, by interpolating the minima and maxima independently, that sandwich the data. Information is propagated about local oscillations to all pixels in the image. The average of the two interpolants is evaluated at each pixel.This provides an estimate of the local mean about which the oscillations occur. The interpolants are to be edge preserved in the traditional sense so that they retain fidelity to the input at strong gradients.

Our smoothing algorithm consists of three steps:

- Identify of local minima and local maxima of I.
- Interpolate the local minima and maxima to compute minimal and maximal extremal envelopes respectively.
- computation of the smoothed mean M as the average of the extremal envelopes.

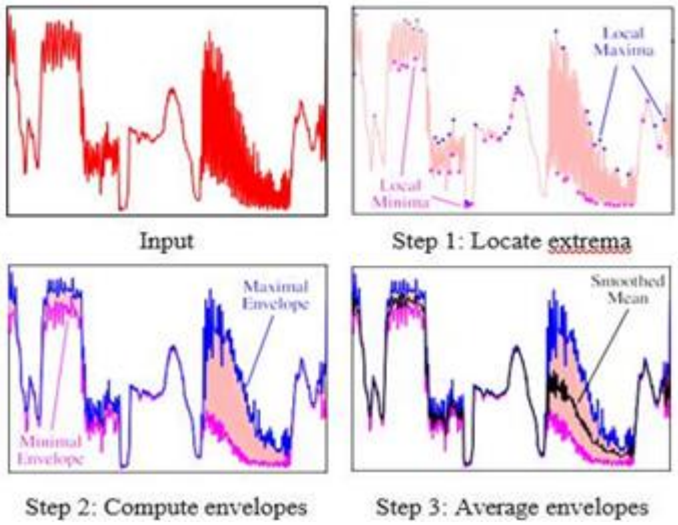

Figure 4: The three steps of our smoothing algorithm is illustrated along the row . Step 1: locating the local minima and maxima of the input (red). Step 2: determine the minimal (magenta) and maximal (blue) envelopes as edge-preserving interpolants with the min- ima and maxima . Step 3: Computing the average as smoothed mean .

Figure 4 illustrates the three steps of our smoothing algorithm.by plotting 1D slices of the Barbara input image (red), its extrema, extremal envelopes (blue and magenta) and smoothed mean (black). D = I − M is the detail layer obtained.

Extrema location: Pixel p is reported as a maxima if at most k − 1 elements in in the k × k neighborhood around p are greater (resp. smaller) than the value at pixel p. Oscillations whose max- ima are detected by using a k×k kernel have wavelengths of at least k/2 pixels. Intuitively, using a large kernel overlooks the detection of fine oscillations. We start with k = 3 and increase the kernel size for multiscalesmoothing,after extracting fine oscillation.

Extremal envelope construction: Given an image I and a set of pixels S (image local extrema), we compute an extremal envelope E using an interpolation technique for image colorization. In our context, we seek an inter-polantE such that neighboring pixels E(r) and E(s) have similar values if I(r) and I(s) are similar. More formally, we minimize the functional

$$\sum_{\mathbf{r}} \left(E(\mathbf{r}) - \sum_{\mathbf{s} \in N(\mathbf{r})} w_{\mathbf{rs}} E(\mathbf{s}) \right)^2 \qquad (1)$$

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subject to the constraint
∀p∈ S E(p) = I(p).

N (r) denotes the neighbors of r, and weights

$$w_{\mathbf{rs}} \propto \exp\left(-\frac{(I(\mathbf{r})-I(\mathbf{s}))^2}{2\sigma_{\mathbf{r}}^2}\right) \qquad (2)$$

are computed using the local variance σ2 around r. We minimize the quadratic functional using their weighted least squares formulation, which reduces to solving a sparse linear system with N (r) defined as a 3× 3 local neighborhood.

Smoothed mean: Performing the envelope construction indepen- dently on the minima and maxima of the image yields the minimal and maximal envelopes respectively. The smoothed mean image is computed as the average of these two envelopes (see Fig 4).

B. Multiscale decomposition

A single smoothing operation of I yields a detail image, D1 , that contains the finest-scale local oscillations and a mean, M1 , that rep- resents a coarser trend. We obtain a multiscale decomposition of the input image by recursively extracting a number of detail layers from the mean. After n recursive smoothing operations, we obtain detail images D1 , D2 , ..., Dn at increasing scales of coarseness and a residual mean image:

$$I(\mathbf{p}) = \sum_{i=0}^{n} D_i(\mathbf{p}) + M_n(\mathbf{p}). \qquad (3)$$

Choosing k = 3 as the size of the extrema-location kernel for the first smoothing step of I results in a detail D1 that captures oscillations of frequency up to 3/2 pixel−1. By increas- ing k, we effectively capture coarser oscillations while recursively smoothing M1 . Progressively increasing k through each recursive smoothing causes the different detail layers to contain increasingly coarse oscillations. In our experiments we found that the algorithm was not sensitive to the factor by which k was increased. For all the results in the paper we increased k by a constant value of eight, between iterations. Figure 5(d) visualizes the extrema of I, M1 and M2. For compact visualization, the three sets of extrema are shown in different vertical regions of the image.

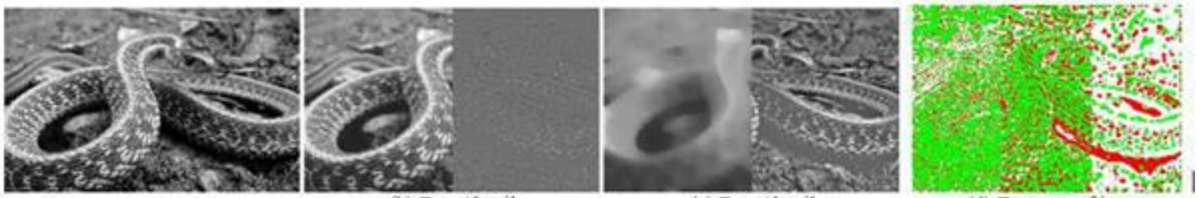
(a) Input image (b) Base/detail after one smoothing operation (c) Base/detail after two smoothing operations (d) Extrema of input and two base layers (b) and (c)

Figure 5: The local extrema of the input image, base layer in (b) and the base layer in (c) are shown as three abutting vertical regions in (d).

3. RESULTS AND DISCUSSION

Noise effection: If our input images is noisy, if the scale of the noise does not match the scale of input image features our algorithm separate the noise.Repeated an experiment on a greyscale image with several step-edges

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of varying magnitude that polluted noise at two scales.By using our decomposition algorithm it recovers the noise at different scales (see Fig 6).

Preservation of edge: Consider edges regions; where the variation in the neighboring extrema value is large.preservation of edges take place using our smoothing filters,because the extremal envelopes maintain accuracy to the pixels data here also nearby extrema value is large. Large-amplitude regions are smoothed effectively since the local extrema have similar values.

Image scaling robustness: The scaled version decomposition of an image provides consistent results if the window used for extrema detection is scaled accordingly.The kernel size used in our extrema detection serving to decide the largest frequency of oscillations that can be extracted asdetail.

Sparse-extrema: If the local extrema density is very low, the interpolation can become unstable. Low extremal density point out that the underlying function is very smooth. By Introducing artificial interpolation constraints in smooth regions makes the interpolation stable.

Smoothing based on contrast reduction: The edge-preserving interpolation scheme that smoothed mean preserve isolated discontinuities. The large gradients interpolation for preservation may result in incomplete smoothing of oscillation. By increasing the window size for bothextrema location and performing the decomposition in the log-domain make this effect or repeat each smoothing step until the detail is completely extracted.

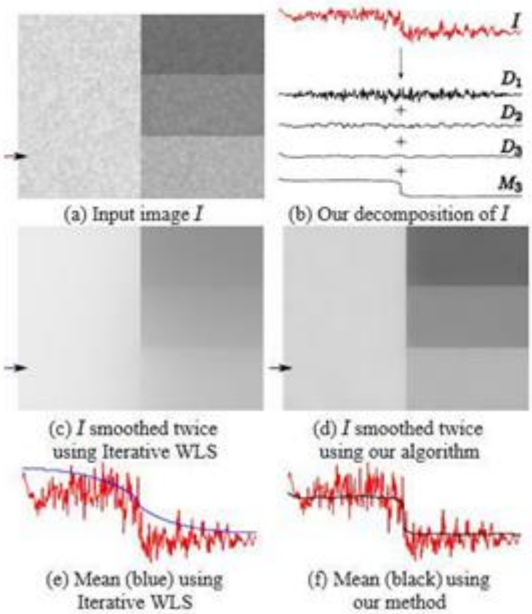

Figure 6: (a) The input image I to which noise was added at different scales.The result of our decomposition(b) on a single row. The result of smoothing (c) using our algorithm. (e) A plot of the smoothed result (blue) using WLS filtering, along with the input (red). (f) A plot of the our smoothed result (black) with the input (red).

Textured regions features at its boundaries: If the boundary oscillation having large amplitude of textured regions are indistinguishable from edges. Figure 7 indicate an example where, despite the high contrast, the spotted pattern is smoothed while the shading is preserved on the coarse scale. So the bright spots at the boundaries are mis- taken. For these kinds of cases require importent information such as from an explicit pattern matching algorithm

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Figure 7: Despite the high contrast, the spotted pattern is smoothed while the shading is preserved on the coarse scale

The smoothing and decomposition algorithms of ours tested on a variety of images. On average, a four layer decomposition of 1025 × 767 images took about 31 seconds using a solver for computing the extremal envelopes and byUsing a simple multi grid solver achieve a speedup of about 1.6. For lacating the locate extrema, we use a 3×3 kernel by a constant value(8 through the recursion for coarser layers.

A. Comparison

We compare the difference between current algorithms and our approach. Our idea definition details the repetative oscillatory features between local extrema which produces different decompositions from existing solutions that elucidate large gradients as edges to be preserved. The differences are, coarse-scale have low contrast features and fine-scale have highly contrasted features.

Low contrast features techniquesextract detail, typicallygive a practical exhibition and explanation of their utility using images where the low contrast detail also tends to be fine-scale. On such images, the difference in results are quite similar since fine-scale features extracted by our technique also happen to be of low contrast. For example, given the flower example(see Fig 8)we successfully bring about similar results.

Figure 9: (a)input image .Fine scale enhancement (b)using WLS (c)our technique

Figure 9 shows an example where the input texteres that is more contrasted than some edges. ByUsing a purely gradient dependent approach, smoothing the oscillationsmoothes low-contrast edges. But the current decompositions involve no ability to understand manipulation of input parameters across different images. By comparing to traditional approaches our technique is simple, smoothes texture, respects soft, single edges, preserves subtle shading and consistently smoothes a variety of images with widely different contrasts.

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Figure 9: Gradient-based techniques cannot preserve subtle, coarse features while smoothing while our method can preserve subtle shading and effectively smoothes the texture.

B. Applications

We have been using multiscale decompositions of images, into layers of varying contrast, in several applications including equalization and image abstraction. In addition to these, we present applications that exploit a key property of our decomposition— the extracted layers correspond to superposed oscillations of increasing coarseness. We apply our decomposition to enhance and to remove detail .

Hatch to tone: while preservivg edges,Few techniques are able to recover tone from images with hatching or stippling.Retaining edges is difficult during smoothing of high-contrast variation. By examing figure 10 the residual from three iterations of our smoothing algorithm on a cross-hatched input image can be determined. We done smoothening of fine-scale oscillations in earlier process.In the case of non-homogeneous high contrast oscillations, the edge preserving nature of the non-linear causes the contrast to be reduced. The residual oscillations amplitude depends on its original wavelength. While smoothing variation, the edges of variations are well preserved and then we compare our solution with a median filter. The problem is that, using a small size, tone is not recovered at a coarse scale and Increasing the kernel size wipes out thin features like outlines. Another drawback of this median filter is that the filter only selects pixel levels that are present in the input image.

Separating fine texture and coarse shading:If the oscillations and shading area of texture are of different scales makes it possible to separate fine textures from shading. Although we make the same assumption that illumination information is “lower frequency” than texture, we do not make any assumptions on the contrast of the texture. Since the bilateral filter, they are prone to the additional assumption that the contrast of the texture and shading are vastly different. We demonstrate the effectiveness of our algorithm by retexturing an image containing high-contrast texture, while retaining shading on the newly painted texture (see Fig. 11).

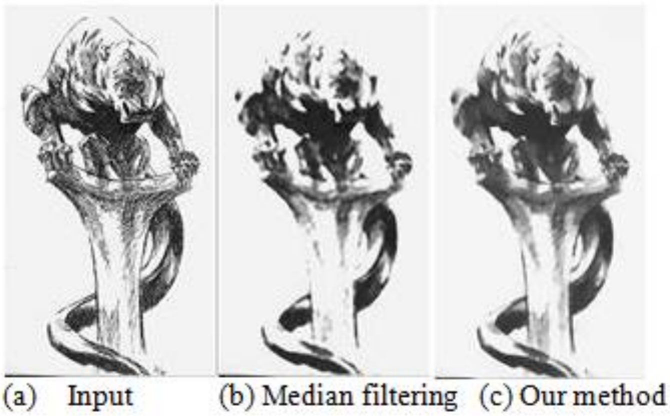

Figure 10: (b) A median filter has two disadvantages: A large kernel size elemenates thin edges while a small kernel size does not smooth the hatched pattern, the median filter selects cannot produce intermediate shades of grey levels only select one of the existing grey level. (c) After three iterations of smoothing the residual exist by using our algorithm yields a good estimate of the tone while preserving the edges of hatched regions.

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Figure 11: (a) Input image (b) Illumination transfer onto painted texture

Image equalization:By considering different linear combination of layers of our decomposition, we show that detail at different scales can be exaggerated. In practice, we perform the linear combinations in log space since we manipulate the log-luminance channel. Current equalization techniques define detail as low contrast. Instead, we are able to control relative contrasts of features based on their scales (see Fig.1).

High dynamic range (HDR) images: Filters such as WLS and bilateral filters,that extract detail based on contrast are more appropriate tools for tone-mapping,We find that our equalizations produce reasonable results (see Fig. 12). Intuitive and consistent parameter values across different images are advantages f our method. Since we filter based on scale and not contrast, specialized techniques are preferable for input where the HDR content is spread across significantly different spatial scales.

Figure 14:(a)Tone-mapped using the bilateral filter(b) Tone-mapped using the WLS filter(c) Our equalized result

4. CONCLUSION

We have presented a definition for detail as oscillations between local minima and maxima.Our definition of detail captures the scale of spatial oscillations, locally,while existing decomposition algorithms extract detail based on a notion of contrast,We proposed a simple algorithm for smoothing input image.Performing the smoothing recursively with extrema detection at multiple scales, we performed a decomposition of the input image into multiple-scale layers of detail. Our algorithm notonly smoothes high-contrast textures but also preserves salient edges. Finally we apply our decomposition in a variety of applications.

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