ShadowWolf: an Algorithm for Clarifying Images Collected Through Atmospheric Fog, Smoke and Dust

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ABSTRACT:
We describe a new algorithm for enhancing texture in very low-contrast regions of an image. The result is a clarified image that retains the overall appearance of the original, but displays additional fine detail. A beneficial effect of the algorithm is the ability to see through atmospheric scattering, such as moderate fog, smoke and dust. It has application to remote sensing and is more effective than alternative approaches.

KEYWORDS: image clarification; texture enhancement; remote sensing; atmospheric scattering.

1 INTRODUCTION

In certain situations information must be obtained from images where details are partially obscured by fog, smoke or dust. For example, Figure 1 shows a NASA image of the surface of the planet Mars under partial fog. It would be quite expensive to obtain another, clearer photo. Our ShadowWolf algorithm applied to the image (Figure 2) enables the planetary scientist to see and evaluate details beneath the atmospheric scattering caused by the vapors.

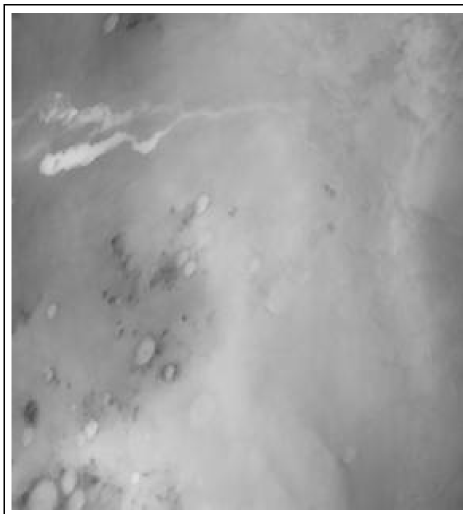


Figure 1. Surface of Mars Obscured by Fog

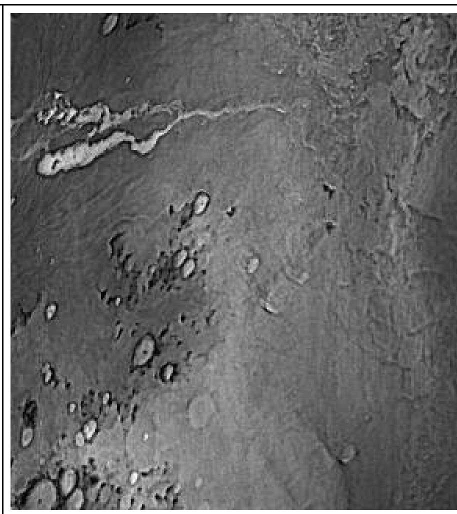


Figure 2. ShadowWolf Applied to Figure 1

While there are many algorithms for edge enhancement and detection, there are relatively few approaches to enhancing the more subtle texture of an image. Contrast enhancement, histogram equalization, and unsharp mask are well known general techniques. Their results are compared to ShadowWolf in Section 4.

Texture variation plays an important role in identifying surface anomalies in a wide variety of objects, such as bruised flesh, and in tracking motion in slowly deforming plastic surfaces, such as ocean swells. Texture also provides a visual context for the understanding of lines. As the example images below display, enhanced texture can make both lines and shadings appear clearer.

While there are new imaging collection modalities, such as radar, synthetic aperture radar, multi- and hyper-spectral, and infrared that can often effectively penetrate fog, smoke and dust, many images continue to use solely visible light. Historical, remote sensed and difficult to obtain images may only be available in visible light mode. It is thus important to develop new approaches to clarify those images in the presence of atmospheric scattering factors. Also, while machine interpretation of images has advanced greatly, human eyes still evaluate many remote sensing images.

The ShadowWolf algorithm enhances texture by adjusting pixel intensity. The adjustment is a non-linear transform using relative variance in a local region combined with a rescaling of dynamic range.

This paper describes related work in Section 2, details the ShadowWolf algorithm in Section 3, examines results in Section 4, and comments on future directions in Section 5.

2 RELATED WORK

There has been little work done on computer vision where weather obscures collected images [9]. Fog, smoke and dust particles interactions with light include scattering, absorption and emission. Detailed modeling has been done on how aerosols affect light [1, 9, 10, 11]. Atmospheric Wiener and Kalman filters have been developed for "clear" weather blur and white noise [1, 2, 3, 14]. However, for images partially obscured by fog, smoke and dust, the common clarification techniques date from early digital image processing – contrast adjustment, histogram equalization, and unsharp mask [2, 10, 14].

Contrast adjustment is a standard image processing technique that applies a remapping of the mid-range intensities to increase distance from the central value while applying other re-mappings in the extrema ranges to reduce intensity differences. [10, 13, 14]. Implementations include both piece-wise linear and "S-curve" maps. The technique works well where the information in the image is known *a priori* to be displayed in the mid-range intensities or where the intensity range of the image does not consume the entire dynamic display range. However, perception of information in extrema intensities will be reduced [14].

Another standard image processing technique, histogram equalization, assembles a cumulative histogram of pixel intensities in the image and then attempts to remap intensities into equal count groupings. Implementations can allow the remapping to apply non-linear mappings as well as the standard constant mapping [13, 14]. The most common implementation using a constant mapping does not require parameter settings. The technique can produce undesirable artifacts, depending on the relative location of pixels. These include the loss of contrast and pixelization noise due to gaps between gray scale units produced by the remapping. A key failing of histogram equalization is that it ignores information about the distribution of intensities within a local region of an image. One approach is adaptively growing regions' boundaries where local histogram equalization can be applied, but the requisite region segmentation slows the results [4, 13].

The unsharp mask technique is a standard image processing technique that sharpens an image by first creating a blurred version of an image using a blurring kernel, often a Gaussian kernel, and then subtracting a fraction of that blurred image from the original [13]. Applying a kernel on a small window enhances fine edges; applying a kernel across a large window and reducing the fraction produces the effect of reducing general haze in the image. Parameters include choice of kernel, kernel size, and fraction. Some implementations include clipping thresholds. Unsharp mask is a widely used, general purpose sharpness enhancement and haze reduction technique [10].

When images are collected in multiple channels or spectra, it is sometimes possible to identify channels with more clarity, or to process groups of channels as linear combinations in order to reduce artifacts and improve clarity [14]. Subtractive haze reduction is a standard remote sensing image clarification technique in those circumstances [12].

Where the texture of interest is edges, there are several approaches to edge enhancement and extraction: Sobol, Canny, Prewitt, Frei-Chen and many others [2, 13]. Many are gradient detectors computed by convolution with a specific kernel. They produce gray scale images with stronger gradients mapped to higher intensity pixel values. False color is sometimes used to emphasize gradients. A disadvantage of these techniques is that they need to be displayed distinct from the underlying image because the semantics of intensity in the two images differ. For example, a strong gradient from black to dark gray is displayed in the gradient image the same as a strong gradient from light gray to white. Also, gradient edge detection results improve where subtle textures are de-emphasized in the image.

The limits of human visual sensitivity also play a role in texture perception and the subjective clarity of an image [6]. Intensity values similar in 8-bit value are imperceptible. Simply increasing contrast, that is the difference between like values, provides a perception of clarification [10]. Textures play important roles in some automated segmentation techniques [5, 7, 8] and texture enhancement is sometimes included in pre-processing for those techniques. The ShadowWolf algorithm provides a novel way to increase local contrast without losing values at the extrema, thereby increasing texture perception. It is effective where fog, smoke and dust permeate the atmosphere.

3 SHADOWWOLF APPROACH

The purpose of the algorithm is to enhance human perception of subtle textures in images. When the human eye scans a real-world landscape containing both dark and light patches and both gross and fine detail, the eye adjusts to "see into" the interesting portion of the scene. ShadowWolf augments that human visual capability when the eye views images.

3.1 Algorithm Overview

In overview, the algorithm operates by making two important adjustments to pixel value. First, when the region where a pixel is located has little variation, the value of the pixel is adjusted so that its relative variation strength is increased. Second, because increasing variation strength can cause some pixel values to exceed the dynamic display range of the image, the dynamic range is rescaled to accommodate the excess value range. The first adjustment increases the sense of texture within a "bland" region. The second adjustment permits perception of variation in very dark and very light regions. A third, less important adjustment reduces the increase of relative variation strength when the original variation strength is very weak. The effect of the third adjustment is to reduce a noise artifact.

Another way of understanding the algorithm is that it adapts to non-stationarities in the pixel intensity surface of the image by enhancing regions between the non-stationarities. The eye immediately perceives the strong "boundaries" in an image because the mean intensity is significantly different across the boundary. The eye fails to perceive less intense variations or textures on either side of the boundary. The eye also is unable to perceive slight intensity variations in "bland" regions that are recorded by 8-bit (or greater) images. Increasing those variations make them perceptible. Fundamentally, the algorithm uses basic statistical properties of the intensities in a neighborhood of a pixel to transform the pixel value.

3.2 Algorithm Details

The ShadowWolf algorithm is provided in Figure 3. A local neighborhood is selected for each pixel in an image. We calculate the mean and standard deviation of intensities in the neighborhood. We use the Gaussian statistical technique of z-scoring to determine the relative variation of the pixel intensity value relative to the neighborhood. Then a rescaling factor is obtained using a non-linear adjustment. The non-linear adjustment is shown in Figure 4. Next, we calculate a new mean using a rescaling of the dynamic range of the possible pixel intensities. Finally, a new pixel value is obtained from the sum of the new mean and the rescaled z-score. If and when the resulting pixel intensity value exceeds the dynamic display range, the excess pixel intensity is clipped.

Parameters:
r sets the size of the neighborhood of interest. Unit: pixel size unit. Notionally it is the radius.
b sets the extent to which the dynamic range of the images is reduced. Unit: pixel intensity unit. Notionally it is the reduction in range, for example from [0,255] to [b, 255-b].
σ' sets the desired variation in pixel value within the neighborhood of interest. Unit: pixel intensity unit. Notionally it is the new standard deviation.
f sets how rapidly the variation in pixel value increases. Unit: pixel intensity unit. Notionally it is the inflection point at which σ' is achieved. See Figure 4.
Displayable range is $[v_{min}, v_{max}]$. Unit: pixel intensity unit.

for each pixel p with intensity v_p, $p \in$ image I
    consider a neighborhood N of size r around p
    calculate the mean μ and standard deviation σ of $\{v_p\} \in N$
    $z_p = (v_p - \mu) / \sigma$
    $s =$ **getRescale**(σ, σ', f)
    $\mu' = b + (\mu - v_{min}) * ((v_{max} - b) - (v_{min} + b)) / (v_{max} - v_{min})$
    $v'_p = \mu' + z_p * s$
    clip v'_p to $[v_{min}, v_{max}]$

where v'_p is the pixel intensity value produced by the algorithm, z_p is the z-scored value of v_p and s is a scaling factor

getRescale Algorithm:
getRescale(σ, σ', f)
$s = \sigma$
if$(\sigma < \sigma')$
    if $(\sigma < f)$ $s = \sigma' * (\sigma / f)$
    else $s = \sigma'$
return s

Figure 3. ShadowWolf Algorithm and getRescale Algorithm

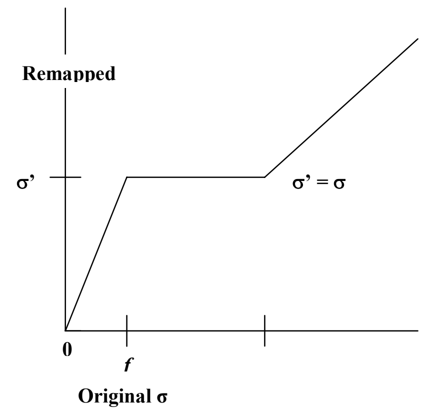


Figure 4. Non-linear Scaling Adjustment for z-scores

Adjustment of the mean compensates to reduce the information loss that can be caused when the z-scoring results in many pixels having values that are greater or less than the displayable dynamic range (for example [0,255] for 8-bit gray). Clipping those values to the extrema {0, 255} would result in information loss similar to that which occurs in traditional contrast enhancement. There are instances where those pixel values contain very valuable information. Examples are the variations of near-white-on-white in sea ice which may indicate uplifts or plastic compressions.

For example with near-white-on-white, if the value range in the neighborhood is [240, 255] the human eye will have difficulty detecting differences in values. Assuming a mean of 248 and a standard deviation of 2, a rescaling of a pixel at +1 standard deviations (that is, 250) with a scaling factor of 10 would result in a value of 268, which exceeds the dynamic range of 8-bit gray. In order to display the rescaled value, we contract the means proportionally away from each end of the dynamic range. In images where little information exists in extreme whites and blacks, the rescaling of the mean can be omitted by setting the boundary parameter to zero.

The computational complexity of ShadowWolf is O(I * N). Assuming I is n x m pixels and N is a square window of (2*r) * (2*r) pixels and calculation of the mean and standard deviation each require a pass through N, the complexity is $O(2 * n*m*(2*r)^2) = O(I * N)$. Because the calculation of the mean and standard deviation of $\{v_p\} \in N$ does not depend on the location of v_p within N, the efficiency can be improved somewhat by implementation of the sliding window of N with a queue batched of columns of length 2*r. Space complexity is O(I+N) since each N can be processed individually.

3.3 Tuning

ShadowWolf uses four tuning parameters. In working with various images, we observed several heuristics for setting those parameters. Parameter settings are affected by the particular type of collection method, camera resolution, image size, and subject matter. Table 1 indicates some tuning considerations.

Table 1. Tuning Parameter Heuristics

Parameter	Useful range	Considerations
r - the size of the neighborhood	5 to 20	A small value produces small detail clarity. An r less than 5 often produces a grainy effect because the neighborhood is too small to support reliable statistical estimates.
b -dynamic range reduction	0 to 60	A small value maintains the original dynamic range of the image, but will cause detail in very white or very black to be lost. A large value will cause the image to have less overall contrast, but will enable display of detail in very white or very black regions.
σ' - the desired variation in pixel value	10 to 100	A small value will be insufficient to enhance textures to the level of human perceptibility. A large value will force very dark and very light pixels to be clipped at the dynamic extrema.
f - how rapidly the variation in pixel value increases	10-25% of σ' and >4	A small value will cause "noise" to appear in regions of very low contrast. A large value will be insufficient to enhance textures in regions of low variation.

ShadowWolf will enhance the artifacts left by .JPEG compression and decompression that are ordinarily invisible to the human eye. These enhanced artifacts should not be confused with valid information content in the image.

Because ShadowWolf will also enhance, rather than remove, the additive Gaussian noise that is used in testing some image clarification techniques, Gaussian noise removal evaluation metrics are inappropriate.

4 RESULTS

We applied ShadowWolf to a wide variety of remote sensed images where human perception of details was affected by weather. We show four sample images where ShadowWolf and competing methods have been applied to improve the human perception of texture and clarify details. The images were collected where environmental conditions included fog, smoke and dust that obscured portions of the scenes. We applied other well known methods for comparison. These included histogram equalization, contrast adjustment, and unsharp mask.


a) original

b) contrast adjustment

c) histogram equalization

d) unsharp mask

e) ShadowWolf

Figure 5. Dust Storm – Bagdad, Iraq. Original jpeg 640x749 pixels


a) original

b) contrast adjustment

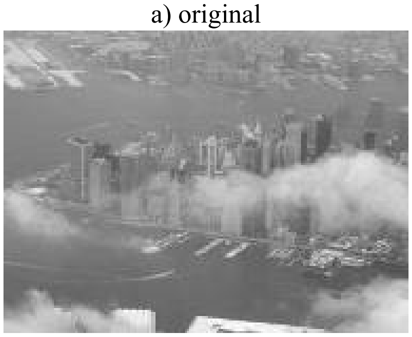
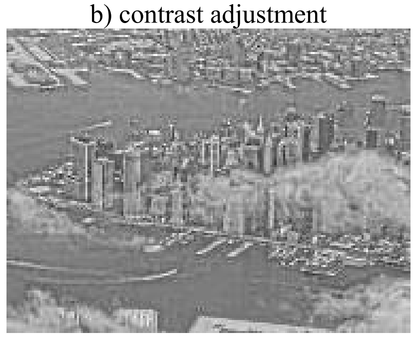
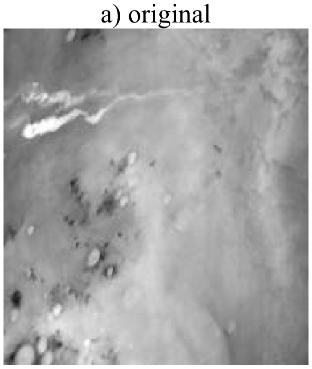
c) histogram equalization

c) unsharp mask

d) ShadowWolf

Figure 6. Fog and Haze – New York Harbor, USA Original jpeg 360 x 270 pixels


a) original


b) contrast adjustment


c) histogram equalization


d) unsharp mask

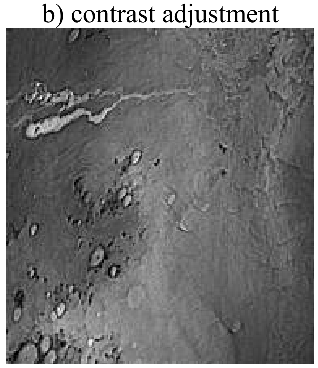
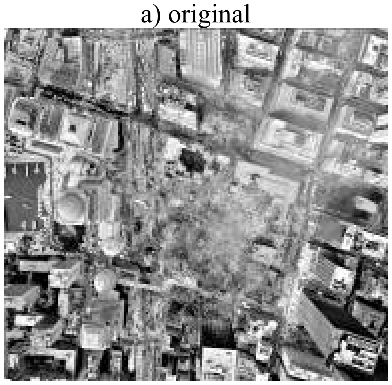

e) ShadowWolf

Figure 7. Fog – Mars Surface. Original jpeg 999 x 1103 pixels. Photo credit NASA


a) original


b) contrast adjustment


c) histogram equalization


d) unsharp mask


e) ShadowWolf

Figure 8. Smoke – World Trade Center site, New York, USA Original jpeg 1371 x 1575 pixels

5 Conclusion and Future Work

We applied the ShadowWolf algorithm to images where moderate dust, fog, and smoke that was present when the images were collected caused image details to be unclear. A noticeable improvement for human perception was observed. Improvement subjectively exceeded that obtained by other well known methods.

We anticipate that ShadowWolf can be useful in other domains such as medical and scientific images, and could be extended to other modalities including electron microscopy and multi-spectral images. It should be possible to parallelize ShadowWolf and perhaps embed in hardware for near real time processing of the image improvement. Finally, research into whether ShadowWolf enhancement of texture will materially aid texture based automated image segmentation and classification may identify other benefits from enhancing texture perception. To the extent ShadowWolf improves human perception of images, it can change the "ground truth" against which machine learning results will be compared.

Recognition: ShadowWolf is named in honor of the Native American trackers who help detect illegal passage across the remote desert boundaries of the United States.

6. References

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