Propagation of Noise Statistics in Digital Photofinishing Image Processing

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Abstract

A highly influential factor in the performance of image processing algorithms is the amount of noise present in the digital image. A priori knowledge of the expected levels of noise in the image dramatically improves the performance and efficiency in image processing routines. In a digital photofinishing system, image noise is primarily attributed to film grain and scanner noise. Therefore, if the film and scanner sources are known, it is possible to deduce the expected noise level in a digital image. However, image processing applied to the image after scanning will affect the noise statistics. In order for the image processing algorithms to deliver optimum performance, the estimated noise statistics need to be modified according to each processing step applied.

We consider image-processing operations as applying transformations to the image data, and corresponding ones to the image noise statistics. We will discuss analytic equations that approximate the propagation of image noise statistics through several basic image transformations, and their interaction with algorithms in a digital photofinishing image chain.

Introduction

Many image processing operations require noise information in order to properly adapt its parameters to the expected conditions. An example of this type of image processing operation is a noise reduction algorithm, such as the one described by Lee [1], that uses a table of noise root-mean-square (*rms*) values for each color record for every signal level. Thus, if the *rms* value is computed for uniform image areas of various signal levels, the set of these values can be seen to characterize the amplitude of image noise in actual scenes acquired using the same image source, as a function of image signal. The *rms* statistics could be used to adaptively discern texture from noise in localized regions of an image.

During the processing of image information in a multistage imaging system, however, noise statistics are usually changed by every operation or transformation applied to the signal. If this transformation of noise statistics is not taken into account, then subsequent adaptive operations will not operate as intended and system performance, usually in terms of image quality, will suffer.

One way to account for the transformation of the non-image information is to estimate it directly at every step in the imaging system [2]. This estimation step could be used in imaging systems where the image processing operations are deterministic and there exists flexibility to process the set of uniform patches. However, it does not account for adaptive transformation of the noise statistics after the estimation step.

In this paper, we assume that having information available about the image statistics provides a potential advantage for improved image quality and system reliability, and reduced computation. Image noise propagation through several common imaging operations is addressed in the article by Burns and Berns [3]. The analysis was not, however, applied to the transformations of noise statistics in image processing systems for use by adaptive algorithms.

Method

A digital imaging system consists of three main elements as depicted in Fig. 1: an image capture device, an image processing engine, and an output device. The image capture device provides the means to digitize the captured scene, e.g., a digital camera, film scanner, etc. The image processing engine provides the means to correct or enhance the digital image via several imaging transform, as depicted in Fig. 2. Each block in the imaging processing engine corresponds to imaging transforms applied to the digital image. The output device provides the means to output the corrected or enhanced digital image, e.g., softcopy display, paper hardcopy, etc. A conventional digital photofinishing system consists of color negative/reversal film plus a film scanner (acting as the image capture device), and a digital printer (acting as the output device) to produce hardcopy prints of the corrected digital image. The image processing engine could consist, as presented in Fig. 2, of a series of sequential operations applied to the digital image. The operations may include:

- Matrix rotations
- One dimensional Look-Up Tables (LUTs)
- Multidimensional Look-Up Tables, e.g., 3DLUTs
- Spatial Filtering
- Adaptive Algorithms

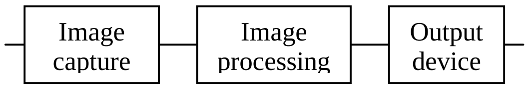

Figure1. Image processing system

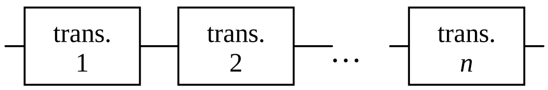

Figure 2. Image processing steps as transformations of the digital image data from input to processed image

Operations such as matrices, LUTs, convolution, etc. do not take into consideration noise present in the digital image. However, adaptive algorithms, such as adaptive noise reduction and adaptive sharpening algorithms, take into consideration the expected amount of noise present in the digital image. We refer to this superset of adaptive algorithms as noise sensitive algorithms. In a digital photofinishing system the source of the noise is attributed mainly to film grain and scanner electronics noise. Therefore, the estimated amount of noise is usually known at the capture stage of the digital photofinsihing system. Knowledge of the noise statistics improves a noise reduction algorithm's capability to discern image content from noise, and do a better job in reducing noise without affecting image texture; or a sharpening algorithm's capability to sharpen image content without amplifying the noise in the digital image.

Image processing engines, including noise sensitive algorithms, need to account for linear transformations applied to the digital image preceding the noise sensitive algorithm modules. Otherwise, the estimated noise at the image capture stage will not be accurate when it reaches the noise sensitive algorithm module, resulting in non-optimal algorithm performance. We propose a scheme as the one presented in Fig. 3. In this digital imaging system, the image processing engine consists of two parallel paths. Path 1 corresponds to the transformations applied to the digital image and Path 2 corresponds to corresponding transformations applied to the image noise statistics. Each noise transformation module in Path 2 has a one to one correspondence with the image transformations in Path 1. In this fashion, the noise statistics used by the noise sensitive module will more accurately represent the expected amount of image noise present in the digital image, resulting in optimal performance and optimal image quality.

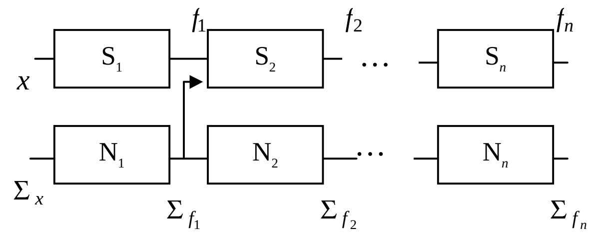

Figure 3. Image processing operations {S}, where the second is noise-sensitive. The image noise characteristics are modified by corresponding transformations {N}.

Referring to Fig. 3, we now use methods for the propagation of image noise statistics in a digital photofinishing system. The mathematical formulations presented correspond to a limited representative subset of imaging transforms, namely matrix operations, 1D LUT operations, and 3D LUT operations. These noise propagation formulations represent practical approximations. For more details on the source of these approximations refer to Ref. 3.

Noise Propagation Techniques for Several Imaging Transforms

The influence of several common image processing operations on image noise will now be described, with emphasis on the rms fluctuations and the correlation (or covariance) between color signals. The noise statistics can be stored as table statistics. Consider the set of color signals, **x**. We can represent the second-order statistics as a covariance matrix

$$\Sigma_x = \begin{bmatrix} \sigma_{pp} & \sigma_{pq} & \sigma_{pr} \\ \sigma_{pq} & \sigma_{qq} & \sigma_{qr} \\ \sigma_{pr} & \sigma_{qr} & \sigma_{rr} \end{bmatrix},$$

where $\mathbf{x} = \lfloor p, q, r \rfloor^T$ and the square roots of the diagonal elements of Σ_x provide the rms noise values, and the superscript **T** indicates the transpose. Note that each element of the covariance matrix can be a function of the mean signal levels. In the following, the symbols Σ_i and Σ_{i+1}, will indicate the covariance matrices as a function of signal level corresponding to the noise present in the images $f_i(x,y)$ and $f_{i+1}(x,y)$, after steps i and i+1, respectively.

Figure 3 presents an example of the noise variance terms (σ_{rr}, σ_{gg}, and σ_{bb}) as function of signal. In this case, the signal is represented as film density as measured by the film scanner. For each image transformation $f_i(x,y)$, the corresponding transformation of the image noise statistics, representing the noise transform i, is determined.

Multidimensional Transformation

The multidimensional nonlinear transformation is a general operation, for which several common operations are special cases. If the image transform is a multidimensional function, it may be defined by a continuous function for each image record, as many color-space transformations are. The transformation, **G,** and operates as

$$\mathbf{f}_{i+1} = \mathbf{G}\mathbf{f}_i$$

it can be expanded, for a three-color system, as

$$\begin{aligned} s &= g_1(p,q,r) \\ t &= g_2(p,q,r) \\ u &= g_3(p,q,r) \end{aligned} \qquad (1)$$

where the sets of input and output signals are {*p*, *q*, *r*} and {*s*, *t*, *u*}, respectively. The corresponding covariance matrix transformation is approximated by [5]

$$\Sigma_{i+1} \approx \mathbf{J_G}\Sigma_i\mathbf{J_G}^{\mathrm{T}}, \qquad (2)$$

where $\mathbf{J_G}$ is the Jacobian (derivative) matrix, This is given by

$$J_G = \begin{bmatrix} \frac{\partial g_1}{\partial p} & \frac{\partial g_1}{\partial q} & \frac{\partial g_1}{\partial r} \\ \frac{\partial g_2}{\partial p} & \frac{\partial g_2}{\partial q} & \frac{\partial g_2}{\partial r} \\ \frac{\partial g_3}{\partial p} & \frac{\partial g_3}{\partial q} & \frac{\partial g_3}{\partial r} \end{bmatrix}_{\mu_x} . \qquad (3)$$

Matrix Transformation

If the image transform is a linear matrix [3,4]

$$\mathbf{f}_{i+1} = \mathbf{M}\mathbf{f}_i \qquad (4)$$

this is seen as a special case of Eq. 1, where the derivative coefficients of $\mathbf{J_G}$ are fixed and equal to the elements of the matrix. Thus Eq. (2) becomes

$$\Sigma_{i+1} = \mathbf{M}\Sigma_i\mathbf{M}^{\mathbf{T}} \quad . \qquad (5)$$

One-dimensional Continuous Transformation

If the image transform is a one-dimensional nonlinear transformation, it may be defined by a continuous function for each image record, as many color-space transformations are. The transformation, **G,** and operates as

$$\mathbf{f}_{i+1} = \mathbf{G}\mathbf{f}_i$$

now the expanded form of Eq. 1 is

$$\begin{aligned} s &= g_1(p) \\ t &= g_2(q) \\ u &= g_3(r) \end{aligned} \qquad (6)$$

The corresponding covariance matrix transform is still given by Eq. 2, but now the off-diagonal terms of $\mathbf{J_G}$ are zero.

One-dimensional Look-up Table

If the image transform consists of a one-dimensional LUT, this can be seen as a discrete form of the above one-dimensional function. If so, the three diagonal partial derivative elements of $\mathbf{J_G}$ can be approximated by

$$\frac{\partial g_1(p,q,r)}{\partial p} \approx g_1(p,q,r) - g_1(p-1,q,r) \qquad (7)$$

or

$$\frac{\partial g_1(p,q,r)}{\partial p} \approx \frac{g_1(p+1,q,r) - g_1(p-1,q,r)}{2} \qquad (8)$$

or other similar digital filter , where the discrete signal take on integer values, {0, 1, 2…}. The transformation of Eq.2 can be accomplished by first estimating non-zero diagonal elements of $\mathbf{J_G}$.

3.4 Multidimensional Look-up Table

If the image transform consists of a multidimensional LUT, such as a 3DLUT, it can be seen as a discrete form of the Eq. 2. If so, the partial derivative elements of $\mathbf{J_G}$ can be approximated by discrete differences of Eqs. 7 and 8, except that now all six elements are needed for Eq. 2.

Example Noise Propagation

Consider the image processing system of Fig. 1, where the image capture stage results in the rms image noise characteristics (shown in Fig. 4), for a given color-record. The mean (signal) and RMS (noise) data are given in terms of a ten-bit encoded signal [0-1023] scale. This noise characteristic can be taken as the result of photographic film and scanner, or digital camera. Digital mages acquired in this way are then processed using an image processing chain, as in Fig. 3, where one step is noise-sensitive. This step, S_2, may require an explicit noise table as described above, or have an implicit sensitivity based on general noise level.

In the example system, the first image processing step is a one-dimensional LUT aimed at, e.g., improving the estimation of scene exposure. Note that such a table is often computed from scene statistics and, therefore, varies from image to image. This LUT is described in Fig. 5. When the image is processed using this table the corresponding transformation of the image noise characteristics is via Eq. 8. The derivative array was simply computed from the LUT. The resulting image noise data are shown in Fig. 6.

The amplification of the rms noise for low signal levels has easily been computed without requiring estimation from the image data. Subsequent processing steps can account for this by e.g., modifying spatial processing such as sharpening, noise reduction, and compression.

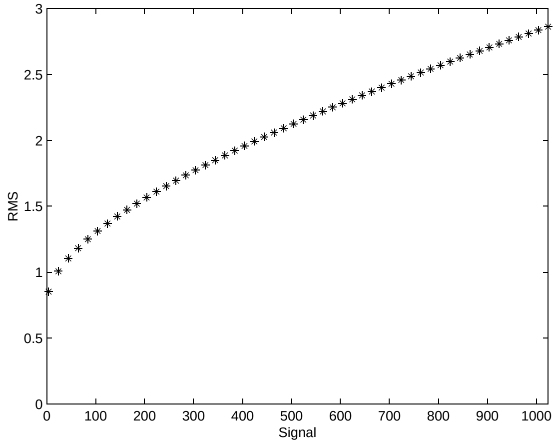

Figure 4. Example input image noise characteristics

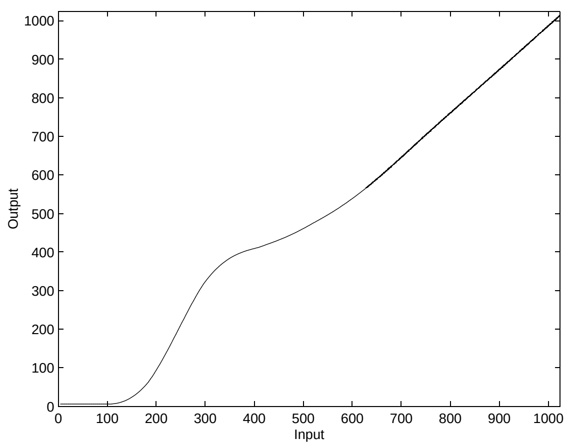

Figure 5. Look-up table applied as the first image processing step

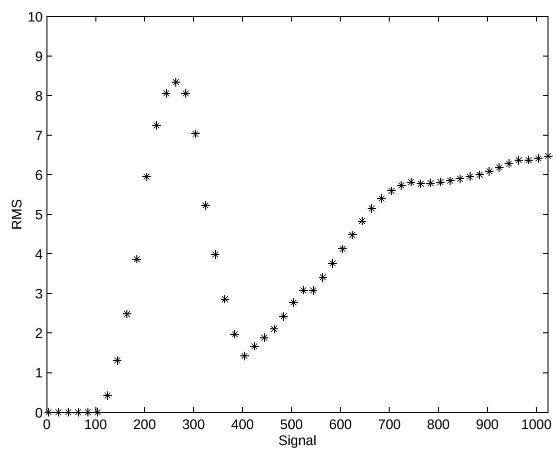

Figure 6.. Modified image noise characteristics

Conclusions

Image processing steps can be thought of as applying transformations to both image signal and noise characteristics. The propagation of noise statistics, in the form of noise tables for several common operations has been described. For multistage photofinishing and other scene-adaptive systems, this approach provides a tool for design and optimization of explicitly noise-sensitive steps. In addition, it is useful in supporting rules based on general image noise levels, and digital image sources.

References

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Biographies

Alex López-Estrada received his BS in Electrical Engineering from the University of Puerto Rico in 1996, and his MS in Electrical Engineering from Rochester Institute of Technology in 1999. He is currently working with Intel Corporation at the Consumer Media Technology Lab in Phoenix, AZ. Previously he was with Eastman Kodak Company.

Peter Burns studied Electrical and Computer Engineering at Clarkson University, receiving his BS and MS degrees. In 1997 he completed his Ph.D. in Imaging Science at Rochester Institute of Technology. After working for Xerox, he joined Eastman Kodak Company Imaging Research and Development organization. His technical interests include; system evaluation, simulation, and the statistical analysis of color error in digital and hybrid systems.
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