Computer Assisted Image Analysis for Objective Determination of Scanning Resolution for Photographic Collections – An Automated Approach

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Abstract

In this paper we present methodologies for using automated image analysis to determine levels of information content for photographic collections and a corresponding spatial resolution for digitization. The approach described is an extension of work in the paper "Establishing Spatial Resolution Requirements for Digitizing Transmissive Content: A Use Case Approach" presented at Archiving 2011.

1. Introduction

Image sharpness is an important factor of image quality, which is also an indicator of image resolution. A variety of sharpness measurements have been proposed, including both subjective [1] and objective metrics [2, 3, 4, 5, 6], among which modulation transfer function (MTF) [2, 3] or spatial frequency response (SFR) are the most commonly used. MTF is defined as the modulation ratio of the output image and the ideal image, and SFR is a measurement of the effective system MTF relative to the test object feature used [8] There are usually two ways to measure the MTF and SFR: using *sine* pattern bar images of different spatial frequencies; and using target board with slanted edges, (an example of GoldenThread Target[1] is shown in Figure 1). In practice, the second method is easier to implement, which computes SFR as the magnitude of the Fourier transform of the point (or line) spread function that is approximated by an idealized edge in the target image. Based on the MTF/SFR computation, Burns and Williams [7] proposed a measurement, sampling efficiency, to summarily communicate true optical resolution to the theoretical maximum as a ratio of the former to the latter.

Currently, sampling efficiency calculation is embedded in commercial software DICE™, which requires user interaction to select the regions of interest (ROI), i.e., regions with clear edges and low noise, for SFR and sampling efficiency computation. This process can be used to determine an appropriate scanning resolution to capture information content. Unfortunately even for experts it is very hard to identify all the features in a photographic image that are suitable for analysis, resulting in large intra- and inter-observer variations. In addition, the time cost to analyze high resolution digital images for large photo collections is very high, making manual analysis an impractical option. In order to overcome these problems, we developed an automated image analysis approach to derive an appropriate spatial or scanning resolution from image statistics, which provides consistent, accurate and fast analysis. With predefined constraints on edges (e.g., contrast, orientation, and homogeneity) and SFR (e.g., curve shape and magnitude), our method identifies all the valid image edges, based on which we compute the SFR and sampling efficiency for each edge. With the center limit theorem, we obtain the final optimal scanning resolution based on the maximum sampling efficiency of each image sample.

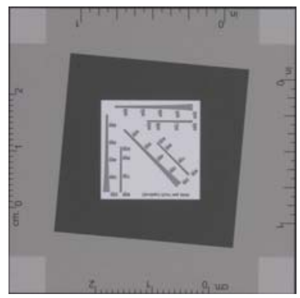

***Figure 1**. Example of slanted edges for MTF computation.*

This paper is organized as follows: Section 2 briefly introduces image quality and sharpness background. Section 3 presents the proposed image analysis approach for automatic spatial resolution determination. Experiment results and statistical analysis on five sets of samples are presented in Section 4. We draw conclusions in Section 5.

2. Background

Image quality is usually assessed by a variety of factors, such as sharpness, noise, dynamic range, color accuracy, distortion, and etc. Image sharpness is obtained by image sharpening techniques that enhance the contrast among subjects in order to convey more details. Image sharpening is usually implemented through image edge enhancement, such as filtering techniques using unsharp masks [8] and anisotropic image diffusion [9].

As introduced above, the most commonly used image sharpness measurement is through the SFR [2, 3]. Given square wave grating of different frequencies *f* (measured by the number of lines/mm), modulation is defined as

$$\text{Modulation} = (I_{max} - I_{min}) / (I_{max} + I_{min}) \qquad (1)$$

where I_{max} and I_{min} are the maximum and minimum intensity measured in the image. The MTF is then defined as a function of the frequency, which is the modulation ratio of the output image and the input (ideal) image at certain frequency. Thus the value

[1] Image Science Associates. http://www.imagescienceassociates.com/

range of SFR is from 0 to 1, and the value monotonically decreases as the frequency increases. However, with image enhancement techniques, images may be oversharpened. This could produce higher SFR values at high frequencies, which corresponds to the phenomenon of "halos" at edges. While the square wave grating-based method requires measurements of modulations for different spatial frequencies of the *sine* pattern bars, a simpler and more commonly used way to derive the SFR employs images with edge gradient analysis using slanted edges, see Figure 1. Given an image edge, an edge spread function (ESF) is first obtained as the profile across it (i.e., a plot of the pixel values). A line spread function (LSF) is then computed as the derivative of the ESF. Finally, the SFR is the Fourier transform of the LSF. An image edge should be a step function but will inevitably not be in practice. Therefore, slanted image edges are usually used in order to produce more samples on the ESF profile for more accurate LTF computation. This is implemented by projecting all points on multiple lines crossing the edge to one line, which produces sub-pixel resolution on the profile. Using such oversampled ESF, we can obtain more accurate results on the LSF and thus the SFR values. Many target boards produced by different companies are currently used for the SFR estimation. In this paper, we use this second method to compute the SFR and the sampling efficiency.

Besides the SFR, other commonly seen image sharpness measurements include subjective quality factor (SQF) [1] and acutance [10]. SQF is a subjective metric, which is dependent on SFR, print or display height, viewing distance, and human eye's contrast sensitivity function (CSF) [11]. Acutance describes image edge contrast, which is usually sensitive to image noise. Recently, more advanced human visual system (HVS)-based metrics have been proposed to characterize image sharpness like human visual perception. For example, the concept of just noticeable blur (JNB) is integrated into a probability summation model in [4], which employs the fact that HVS masks blurriness around an edge up to a certain threshold. Thus the JNB is determined as a function of the local contrast and is used to derive an edge-based sharpness metric that makes use of probability summation over space. This metric is also able to predict image blurriness with different contents. In [5], a local feature is constructed as the ratio of high and low band spatial frequencies in a small neighborhood. Thus adaptive image sharpening can be implemented that enhances image contents based on their sharpness measurement. In [6], a no-reference image sharpness measure is constructed based on the local phase coherence (LPC) in the wavelet domain, i.e., the phase of the complex wavelet coefficients at image edges shows a consistent relationship across different scales. The proposed metric has a broad application in distortions caused by compression, filtering and noise contamination. Last but not least, the interested reader is referred to [4] for an overview of no-reference image sharpness metrics.

3. Scanning Resolution Determination

This section presents our approach to determine the level of information content for photographic collections, specifically B+W photographic negatives, and a corresponding spatial resolution for digitization through image analysis techniques. A

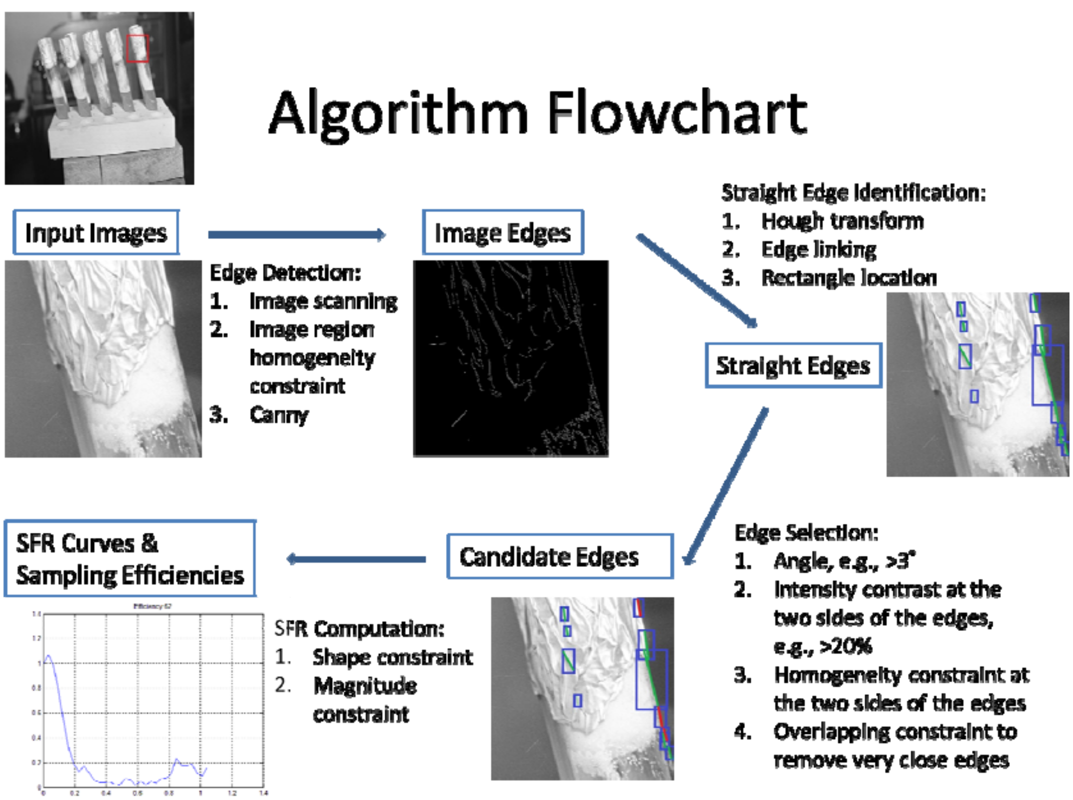

***Figure 2**. Automatic SFR analysis algorithm flowchart*

flowchart of our algorithm is shown in Figure 2, which consists of main functions of valid edge detection, SFR and sampling efficiency computation, and scanning resolution determination.

The images in our collection are generally scanned under a controlled environment with large image size (e.g., 9000 × 7000), which may introduce problems such as nonuniform illumination and exposure. In addition, scanning noise and artifacts also vary across the images. Thus the traditional global approach for feature (edge) detection cannot produce accurate results. In our model, we use a sliding window to "scan" the high resolution digital images of photographs in a block-by-block manner (e.g., block size 1000 × 1000). We skip smooth blocks for high speed processing. For a non-smooth block, straight edges are identified by Canny edge detector and Hough transform. Gaussian smoothing is employed in this step to overcome the noise effect. We also choose the minimum gap among edges and the minimum length of an edge. For each detected edge, a small rectangle region (with aspect ratio ½) surrounding the edge is constructed to determine the edge validity. Certain constraints are set in this step for accurate results:

- Angle constraint: each edge should be slanted, e.g., at least 3º in horizontal or vertical direction.
- Rectangle region constraint: an upright edge should always touch the top and bottom rectangle borders; a flat edge should always touch the left and right rectangle borders.
- Intensity contrast constraint: the intensity at the two sides of the edge should be significantly different, e.g., at least 20% difference between the average values.
- Region homogeneity constraint: the two sub-regions at the two sides of the edge should be smooth, e.g., their standard deviation should be less than 40% of that of the whole image.
- Region homogeneity similarity constraint: the two sub-regions at the two sides of the edge should have similar homogeneity, e.g., at most 10% difference of their standard deviations.
- Region overlapping constraint: there should be no large overlap between two neighboring rectangles, e.g., at most 50% overlapping.

After valid edge identification, we compute the MTF/SFR following ISO 12233. The derived SFR curves are analyzed to further remove invalid candidates. We set the following constraints to identify the final valid edges for image scanning resolution determination:

- The SFR at high frequencies (e.g., above the Nyquist frequency) should be smaller than those of low frequencies, e.g., the mean value of the second half SFR should be smaller than that of the first half SFR.
- The SFR should be monotonically decreasing with the increased frequency, i.e., the SFR value at frequency zero should be the largest and the normalized SFR should have the maximum value 1 at frequency zero. Considering the noise effect in practice, we allow variations of the SFR, and we restrict the maximum SFR to be 1.1 at low frequencies. In addition, we restrict that the maximum SFR value at high frequencies is smaller than the 50% of the maximum SFR value of low frequencies.

With these constraints, we identify valid edges in each image for the scanning resolution determination. For each valid edge SFR curve, the sampling efficiency [7] can be computed as the ratio of frequencies at the 10% and 50% (i.e., at Nyquist frequency) SFR values, respectively. In our collection, the sampling efficiency distribution usually does not fit a normal distribution, thus we resort to the central limit theorem to fit a Gaussian distribution for the mean of maximum SFR values of the samples. We present the statistical analysis of the results in Section 4.

4. Experiments

In our experiments, we tested our approach on seven sets of photographic negatives and targets scanned using a variety of scanners with different settings:

- Set #1: FSA safety film negatives — 30 samples scanned on Kodak Eversmart Select at 5000 ppi.
- Set #2: FSA nitrate film negatives — 31 negatives scanned on DT/Leaf Aptus with different resolutions, including 16 negatives of 3"×4" and 4"×5" scanned at 1917 ppi, 7 negatives of 3"×4" scanned at 2377 ppi, and 8 negatives of 2.25"×2.25" scanned at 2481 ppi.
- Set #3: 5 negatives scanned on DT/Leaf Aptus at 1900 ppi and on Kodak Eversmart Select scanner at 3000 ppi.
- Set #4: 4 preservation microfilm targets scanned on Kodak Eversmart Select scanner at 5000 ppi.
- Set #5: 4 preservation microfilm targets scanned on Kodak Eversmart Select scanner at 5000 ppi, with all sharpening and smoothing switches being turned off.
- Set #6: 5 preservation microfilm targets scanned on Kodak Eversmart Select scanner at 5000 ppi, with all sharpening and smoothing switches being turned off.
- Set #7: FSA nitrate film negatives — 86 negatives scanned on DT/Leaf Aptus at 1900 ppi.

Using Set #7 as an example, Figure 3, 4, and 5 show examples of the detected valid edges on one image, the edge regions, and the corresponding SFR curves. We also show the histogram of sampling efficiencies of all the 86 images, see Figure 6. There are 767 valid edges for this sample set, and there are no valid edges found on 7 samples. It can be seen that this histogram is skewed and cannot be fit well by Gaussian model. Therefore, with the central limit theorem, we derive the distribution of the average maximum sampling efficiency as a Gaussian model. The mean of the maximum sampling efficiency is 45.1013 and the standard deviation is 15.2564. Thus the mean and standard deviation of the mean sampling efficiency distribution is 45.1013 and 15.2564/sqrt(86-7) = 1.7165, respectively. We apply the three-sigma rule of the normal distribution to estimate the optimal scanning resolution, i.e., 1900*(45.1013+3*1.7165) ≈ 955 ppi.

Figure 3*. An example of the detected valid edges on an image from Set #7.*

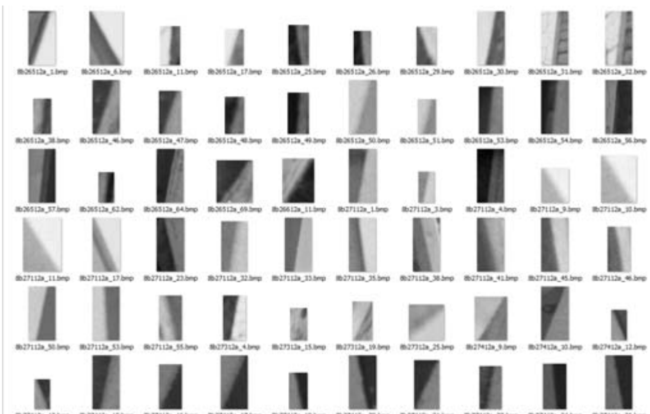

Figure 4*. Sample edge regions from the Figure 3 edges.*

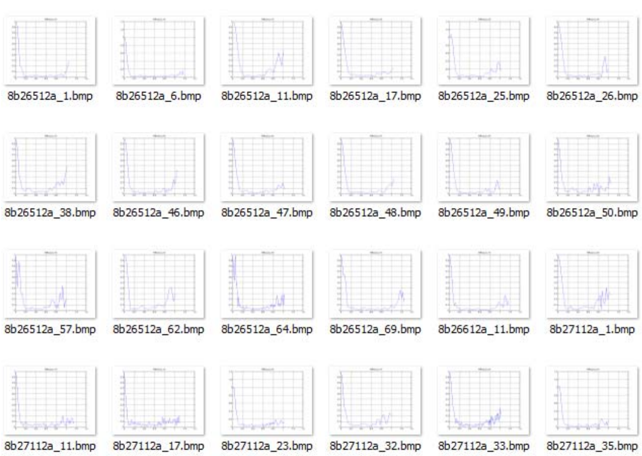

Figure 5*. Sample SFR curves from the Figure 3 edges.*

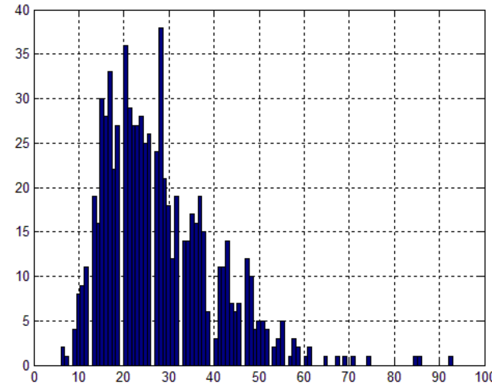

Figure 6*. The histogram of the sampling efficiencies of Set #7.*

In the end, we conducted experiments to verify that our method measures the informational content of the photographic film, which should not be affected by our scanner resolution settings. We scanned a selected set of negatives (five 35mm films) using a comparable scanner (Kodak iQsmart3) using three different resolutions, i.e., 2000, 3000 and 4000 ppi. We then repeated our experiment to derive the average maximum scanning resolution on these three settings. Due to the small number of samples, we did not apply the three-sigma rule here to compute the optimal scanning resolution. Instead, we considered only the mean of the maximum scanning resolutions, which are very close (1635ppi for the set scanned at 3000ppi and 1590ppi for the 4000ppi set), which verifies that our method is independent of the scanner's settings. Note the estimated resolution for the 2000ppi set is 860ppi, which is different from the other two sets. We believe this is caused by the low sampling efficiency of the scanner at this spatial resolution setting, i.e., the measured resolution of the scanner is too low and very close to the frequency of the informational content of these sample photographic negatives.

5. Conclusion

We propose an automated approach for determining spatial resolution for digitization through image and statistical analysis techniques. Our approach searches all valid edges meeting the predefined constraints in a given image, based on which the SFR and sampling efficiencies are computed for all the edges. We repeat the process for all samples in our collections, representative of the age, quality, and variations of the original photography, and apply the central limit theorem to derive the optimal spatial resolution for digitizing each sample set. Experimental results show that our approach is robust and can achieve accurate performance. For future work, we will further investigate the robustness and accuracy of our method on more comprehensive collections with larger sample sets.

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Author Biography

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Don Williams worked as a research imaging scientist for Kodak for 25 years until he left to form his own company, Image Science Associates, in 2006.. He has published extensively on both technical and policy matters as they relate to digital image fidelity and metrology Don is also the editor for ISO 12233, 2nd edition, Spatial Resolution Measurements, Digital Still Cameras, and has acted as co-leader for equivalent performance standards on reflection and film scanners