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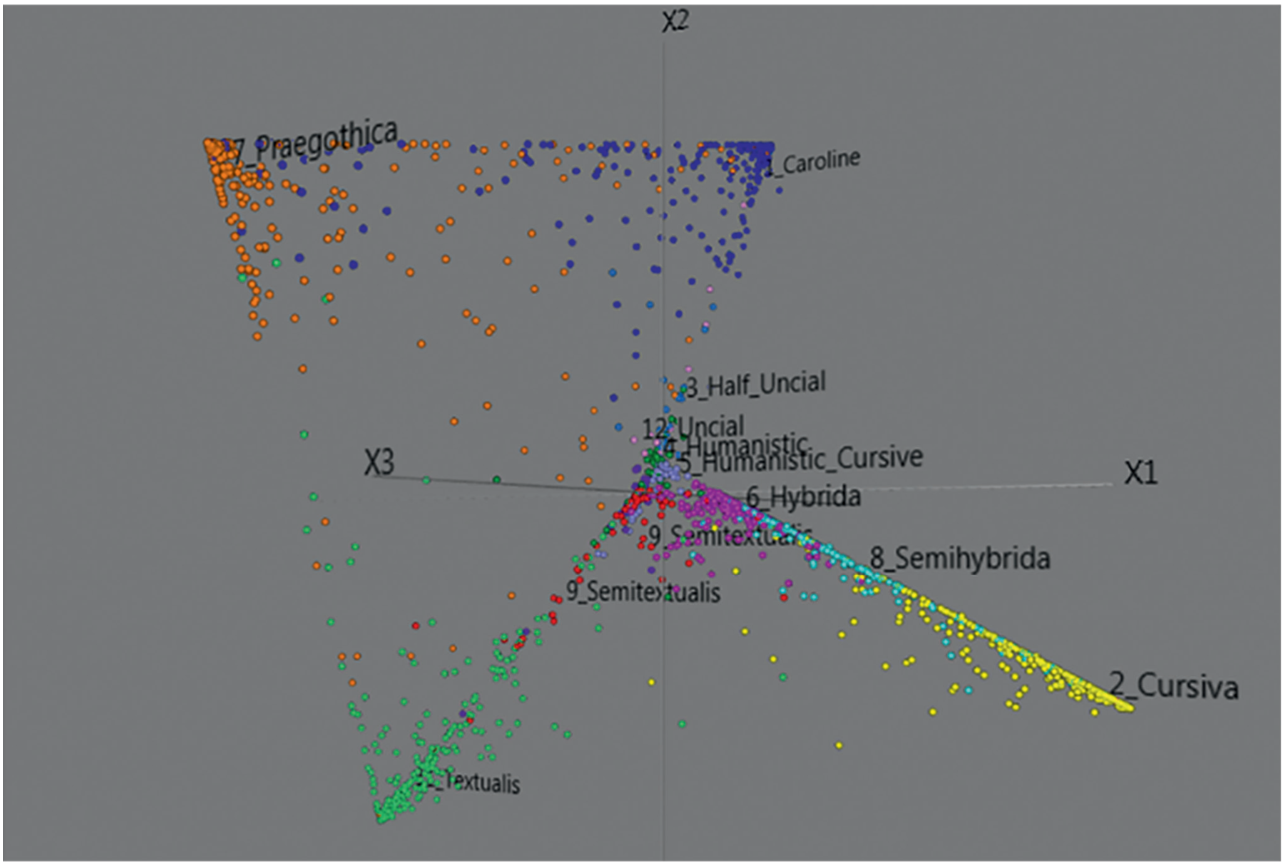

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CONTENTS

Article

Image Quality in Cultural Heritage

Tyler R. Peery, Roger L. Easton Jr., Rolando Raqueno, Michael Gartley, and David Messinger | Rochester, NY

Abstract

The application of modern spectral imaging technologies to recover information from cultural heritage objects, such as erased or damaged text in manuscripts, has become quite common in the last two decades. These techniques collect images under different wavelengths and modes of illumination (reflection, fluorescence, and transmission) and then combine them digitally to enhance the readability of low-contrast features. Of course, the imaging technologies (e.g., lighting, lenses, and sensors) continue to improve and manufacturers are always tempting users to purchase their newest advances, often without analyzing the costs and benefits of the system upgrades for the imaging tasks at hand. This observation suggests the need for better analysis of the 'chain' of stages in the imaging system to determine the weak points in the system where improvements would be most beneficial. This paper attempts to begin addressing some aspects of this analysis: the tradeoff between optical diffraction and spatial resolution specified by the pixel size. In the paper, system metrics that have been developed and used in environmental remote sensing are adapted for use in cultural heritage imaging and may help provide insight into the value of the parameters of imaging systems.

1. Introduction

In an age of high-resolution digital cameras and video displays, the acceptance and understanding by users of the idea that 'pixels' represent 'images' and of the meaning of the term 'spatial resolution' are improving. However, several assumptions inherent in the concept of 'resolution' of an image are of significant import in more technical applications. Some of these assumptions are based upon a lack of understanding regarding the human visual system, while others fail to recognize benefits of larger pixel sizes. The key takeaway is the time-old lesson: 'more is not always better'.

A decision to use a sensor with smaller pixels separated by smaller distances (a smaller 'pitch') to sample the image of the scene or object more finely assumes that there is some value to the consequent improvement in scene spatial resolution. Such a decision may seem to be intuitively obvious, though if the analysis of the subsequent image processing is included in the image chain, the 'quality' of the resulting image determined in part by the 'signal-to-noise ratio' (SNR) of the image data also is important to the final result. Fundamentally, improved spatial 'resolution' results from measuring light over smaller areas, which affects the number of counted light photons and the digital counts assigned to each pixel. This means that the 'integration time' needs to be considered, particularly with regards to the light exposure applied to the object. Similarly, the concept of 'well depth' and its impact on image dynamic range must be considered, as it is directly affected by pixel size. In addition, the impact of the spatial resolution on object size and aliasing concerns should be investigated if fine sampling is of major import. And finally, hard drive storage should also be considered, as single image files can exceed gigabytes of data for high resolution systems.

A point of diminishing returns can be reached with increased resolution, particularly when paired with the human visual system. If an object was created to be viewed by humans, and is being imaged to convey that same information, then imaging beyond the limits of human vision would not likely be beneficial. The benefits of higher resolution systems can include finer detail and sharper images, which may contend with aliasing and human visual system limits. The costs of higher resolution include increased digital storage space and lower signal levels per pixel, which can sometimes be combatted with increased exposure time or illumination. These benefits and drawbacks, along with their caveats, will be the focus of this paper.

2. Spatial resolution and sampling

Spatial 'resolution' is a term that has become familiar to users of smartphone cameras, though the scientific consideration is somewhat more complicated than the naïve concept. The common understanding is that images with more pixels over the same image area will appear 'better' to the viewer. For

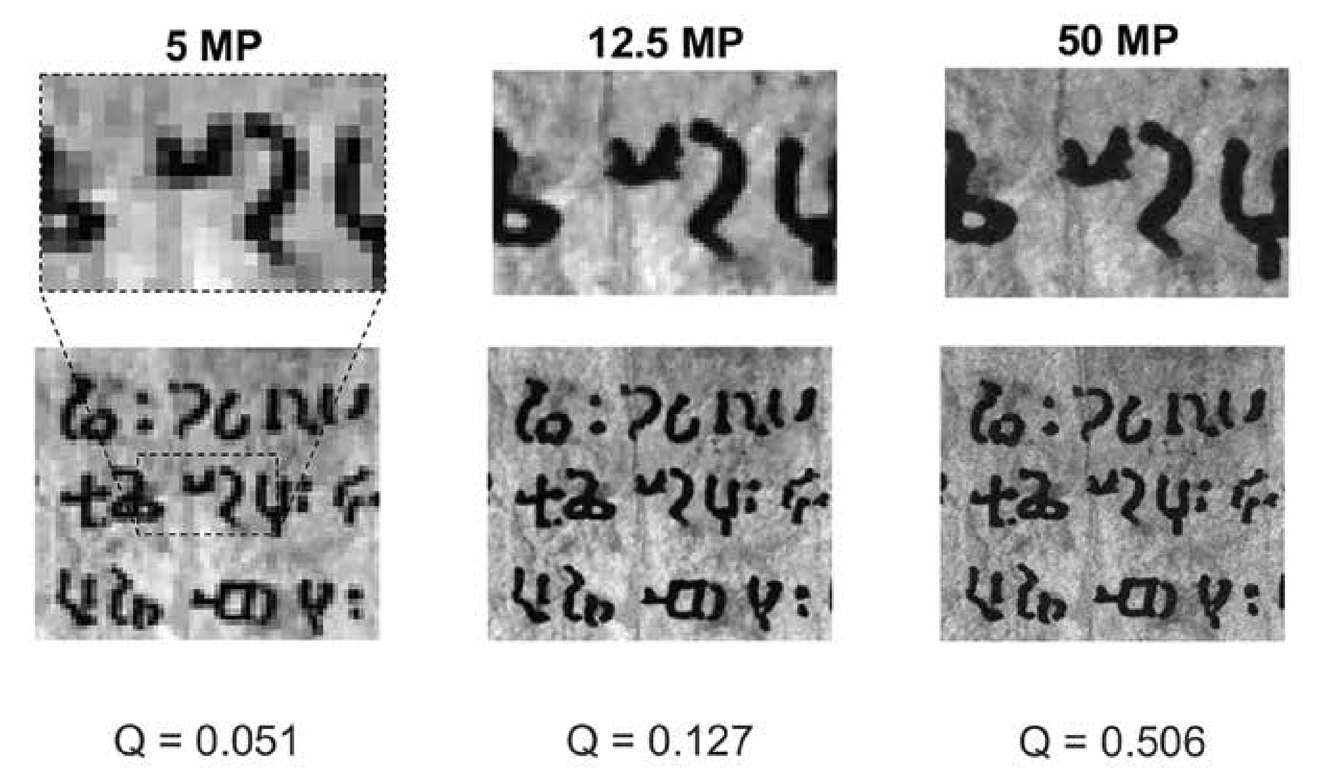

Fig. 1: Effect of decreasing pixel pitch to increase spatial resolution, which produces a 'smoother-looking' image. The gray scale of the images has been scaled by histogram stretching to better illustrate these differences.

example, this will allow the user to 'zoom in' on a feature without seeing the impact of the spatial resolution, often appearing as 'pixilation' or 'blockiness'. The cost of the image having too few pixels is the most intuitive aspect of spatial resolution (Figure 1). The image begins to appear 'blocky' if the user 'zooms in'. However, increasing the resolution can only sharpen an image so much, according to the spatial sampling mentioned in the previous section.

2.1 Target size

In environmental remote sensing, a metric used to determine the required level of image quality based upon target resolution is the 'National Imagery Interpretability Rating Scale' (NIIRS). This scale adjusts linearly with resolution of the intended target of the system, showcasing that increases in resolution and sharpness will be required for successful analysis of finer resolution targets. Just because a system can technically sample at a fine enough resolution, does not mean that the image will be interpretable. For example, if the image is too blurry to distinguish fine detail within texts, then fine sampling will be of little use to the human attempting to interpret it. A further constraint on the system, once the resolution is selected, will be to pair an appropriate diameter of the collection aperture with the pixel separation (known as 'pixel pitch'). The balance of these two will impact sharpness and aliasing of the system, based on a ratio of the cutoff frequency determined by each. Limitations of the human visual system highlight upper limits of sampling (resolution) and impacts of contrast, particularly when the end user is a human attempting to interpret faded texts, and will be reviewed below.

The NIIRS was originally designed for image analysts in the intelligence-gathering community to specify which tasks could be performed using an image with specific collection parameters. As shown in Table 1.[1, 2] the NIIRS produces numerical values from 0-9 and specify typical tasks that may be performed on that data, from detecting large buildings to identifying barbs on a barbed-wire fence. For example, a 'low-resolution' image, where the pixel spacing on the ground (the 'ground sample distance' or 'GSD') is large could be useful for identifying large buildings, but not even for counting pedestrians. An image with a smaller GSD might be useful for identifying cars, but not for reading

[1] Irvine 1997.

[2] Fiete 1999.

Table 1: Example targets at given NIIRS levels and their associated approximate sizes.

N	Example	Linear Dimension	Average	Ratio (N/(N+1))
1	Terrain type (urban, forest, water, runways)	7.9–79.0 m	43 m	1.26
2	Large Buildings (hospitals, factories) major high patterns	18.0–35.0 m (Medium) 37.0–45.0 m (Large)	34 m	2.83
3	Houses in residential neighborhood, orchards	10.0–13.0 m	12 m	1.20
4	Sports courts, barns, silos	8.0–11.0 m	10 m	2.00
5	Large tents, large animals (elephants, rhinoceros)	5.0–7.5 m (elephant) 3.5–4.6 m (rhino)	5 m	4.13
6	Sedan or station wagon, utility poles	4.5–5.2 m , requires 1 m to differentiate vehicle type	1.21 m	5.50
7	Steps on stairway, railroad ties	0.20–0.25 m (8–10 in)	.22 m	1.80
8	Baby pigs, windshield wipers	0.15–0.30 m (6–12 in) 12–20 mm (0.5 in – 0.75 in)	.122 m	9.38
9	Barbs on fence, spikes on railroad tie	< 12 mm (< 0.5 in)	.013 m	**Ratio Avg = 3.51**

license plates. Assessment of whether an image can be used for different imaging tasks was the reason for constructing the 'General Image Quality Equation (GIQE)'. The GIQE uses the specifications of a given imaging system to predict the quality of resulting images in the NIIRS.

One image sensor should not be expected to be used for all targets and imaging conditions, just as a microscope camera would be impractical for imaging an entire document. Therefore, the appropriate range of target sizes and required resolutions should be selected for each set of system parameters. It makes more sense to select a system that is most appropriate to the typical application, and later adjust the system as changes require. In addition, there is no value to increasing spatial resolution beyond a certain point, as the human visual system may not be capable of detecting the difference in the image. Granted, computer systems can bring out the finer details to a level that humans could appreciate more, which returns us to a proper selection of NIIRS values.

2.2 Human perception limits

The human visual system has several limiting factors that preclude seeing beyond specific thresholds. Of these, those relevant to "sampling" and "detection" are most pertinent to imaging system design. For sampling, we are limited to the analogue of the Nyquist frequency of the human eye, which is determined by the spacing of photoreceptors upon the retina. This limit specifies an upper limit of the spatial sampling of the system. Any larger spatial frequencies will be 'undersampled' and appear incorrectly due to 'aliasing'. The second factor of 'detectability' is the minimum difference in gray value of the scene required to be sensed by the human visual system. This value is limited by 'spreading' of the light by ocular aberrations and by the subsequent neural processing, which was designed by evolution to concentrate on the most pertinent information required for survival. For an example of the latter, humans readily notice rapid motion of approaching hazards, while ignoring slower motion or camouflage. The design of the eye-brain system may limit subtle differences in image quality of low and high frequency background noise, which may be very pertinent to computer vision algorithms that do identify and detect those differences.

The Nyquist frequency, ρ_{Nyq}, of the human visual system can be estimated from the spacing of the photoreceptors or by empirical testing. These methods arrive at two similar answers[3], approximately 50-60 cycles per angular degree. To calculate the Nyquist limit for the HVS, the distance d_p between the photoreceptor cones in the region of highest acuity is approximately 3 µm. This angle scales to approximately 5µm per minute of arc or 0.3 mm/degree, on the retina, which translates to about 100 cones/degree. This would allow unaliased sampling of signals of 50 cycles/deg. However, perhaps due to the shape of the cones or neural processing, typical eye tests show that the acuity of an average adult is actually somewhat better: approximately 60 cycles per degree for 20/20 vision[4].

To build upon these factors constrain imaging system design, it is important to specify the purpose of the system. Depending upon the task, the limits of human vision may play a role in image collection. For example, if a multispectral imaging system (MSI) or hyperspectral imaging system (HSI) is to identify handwritten text, resolution beyond that of the human visual system would likely not be necessary. Therefore, given the known distance and focal length of a detector, as well as the average reading distance of a human, a detector's ρ_{Nyq} may be matched to that of the human visual system.

Using an average reading distance of 0.38 m and human acuity limits of 60 cycles per degree, average humans are unable to discern features smaller than 0.111 mm apart.[5] For example, the state-of-the-art MSI system used to image the Enoch palimpsest at the Berlin State Library had a spatial sampling distance determined to be 26 microns/pixel, which is well beyond the extreme limits of human vision and therefore much better than would be expected of handwritten text. If the purpose of the images is to identify and read texts, such high resolution would not be necessary. A lower resolution system with larger pixels and therefore improved dynamic range would exhibit improved SNR or would require less integration time to capture similar SNR values.

[3] Curcio et al. 1990.

[4] Curcio et al. 1990.

[5] Peery and Messinger 2018.

2.3 Optical resolution, diffraction

Light energy emerging from a source physically spreads during propagation, which is known as 'diffraction'. The purpose of the optical system is to collect and 'refocus' this light to create 'images' of the original source points. However, the spreading of the light ensures that the images of two closely spaced point sources in the object will 'bleed' into each other to the point where they may be indistinguishable from the image. This is the ultimate source of the resolution limit of the imaging system. A common approximate rule of thumb for the limiting separation of two point images that may just be resolved is

$$\Delta x \approx \lambda_0 \cdot \frac{f_0}{D_0} = \lambda_0 \cdot f/\# \tag{1}$$

where Δx is the limiting separation of two point images, λ_0 is the dominant wavelength being imaged, f_0 is the focal length of the imaging system, D_0 is the diameter of the lens system, and $f/\#$ is the focal ratio (f/number) of the system:

$$f/\# = \frac{f_0}{D_0} \, . \tag{2}$$

2.4 Q factor

Q is a metric used to compare the spatial frequencies passed by the optics and by the sensor in an imaging system. It can help characterize aliasing as well as general visual sharpness based on that relationship. Q is defined:

$$Q = \frac{\lambda_0 \cdot f/\#}{\Delta x} \, . \tag{3}$$

The two values effectively being compared in Q are the cutoff spatial frequencies of the optics and of the sensor of the system. These are frequencies of patterns beyond which higher frequencies cannot pass without being aliased, being recorded as an adjusted, lower frequency. The optical cutoff frequency, ρ_{oco}, is:

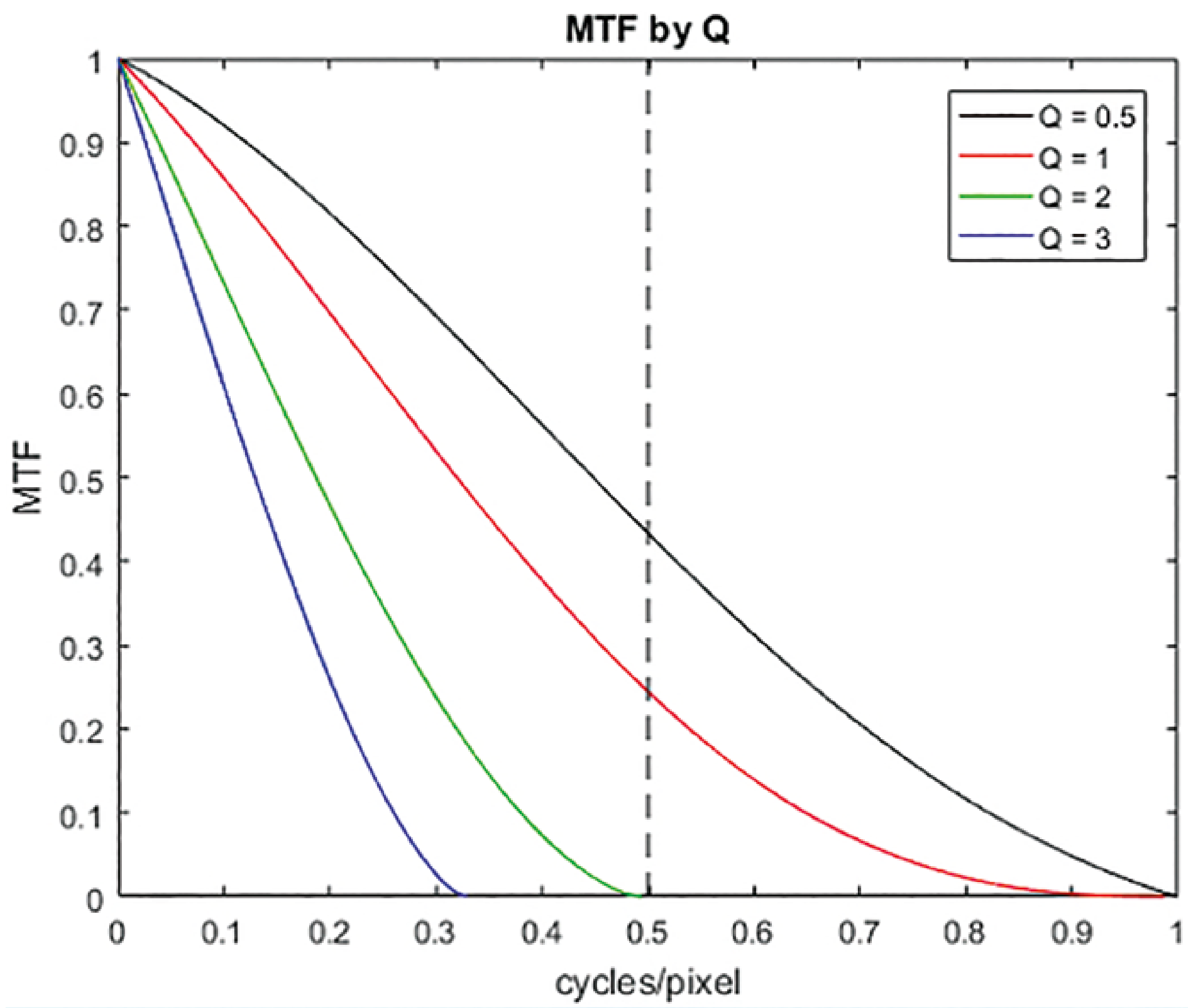

Fig 2: MTF's of various *Q* value systems compared to their Nyquist frequency, normalized to the number of cycles per pixel. Lower *Q* values result in higher frequencies being allowed into the system, resulting in aliasing (right of the dashed line) as well as sharper looking edges.

$$(\rho_{\max})_{optics} = \frac{1}{\lambda_0 \cdot f/\#} \quad (4)$$

The sensor samples the spatial signal from the optics at the pixel spacing Δx, and must sample at least twice per period of every spatially oscillating signal in the scene to avoid aliasing, so the maximum spatial frequency passed by the sensor is:

$$(\rho_{\max})_{sensor} = \frac{1}{2 \cdot \Delta x} \quad (5)$$

This means that for systems where the two maximum frequencies are matched, the definition of $Q = 2$ represents the balance of ρoco matching the pixel pitch's Nyquist limit of ρnyq.

To better illustrate this relationship of cutoff frequencies with the value Q, Figure 2 shows the modulation transfer functions that apply for various Q values. For reference, the Q value for the MegaVision MSI system as captured in Figure 1 had a Q value of 0.5. The Nyquist limit is highlighted by a dashed vertical line.

From Figure 2, it is apparent that the optics in a system with $Q \geq 2$ will not pass spatial frequencies above the Nyquist limit, and thus the image will not be aliased. Systems with smaller values of Q allow larger spatial frequencies to enter the system with less modulation (see Figure 2 where the

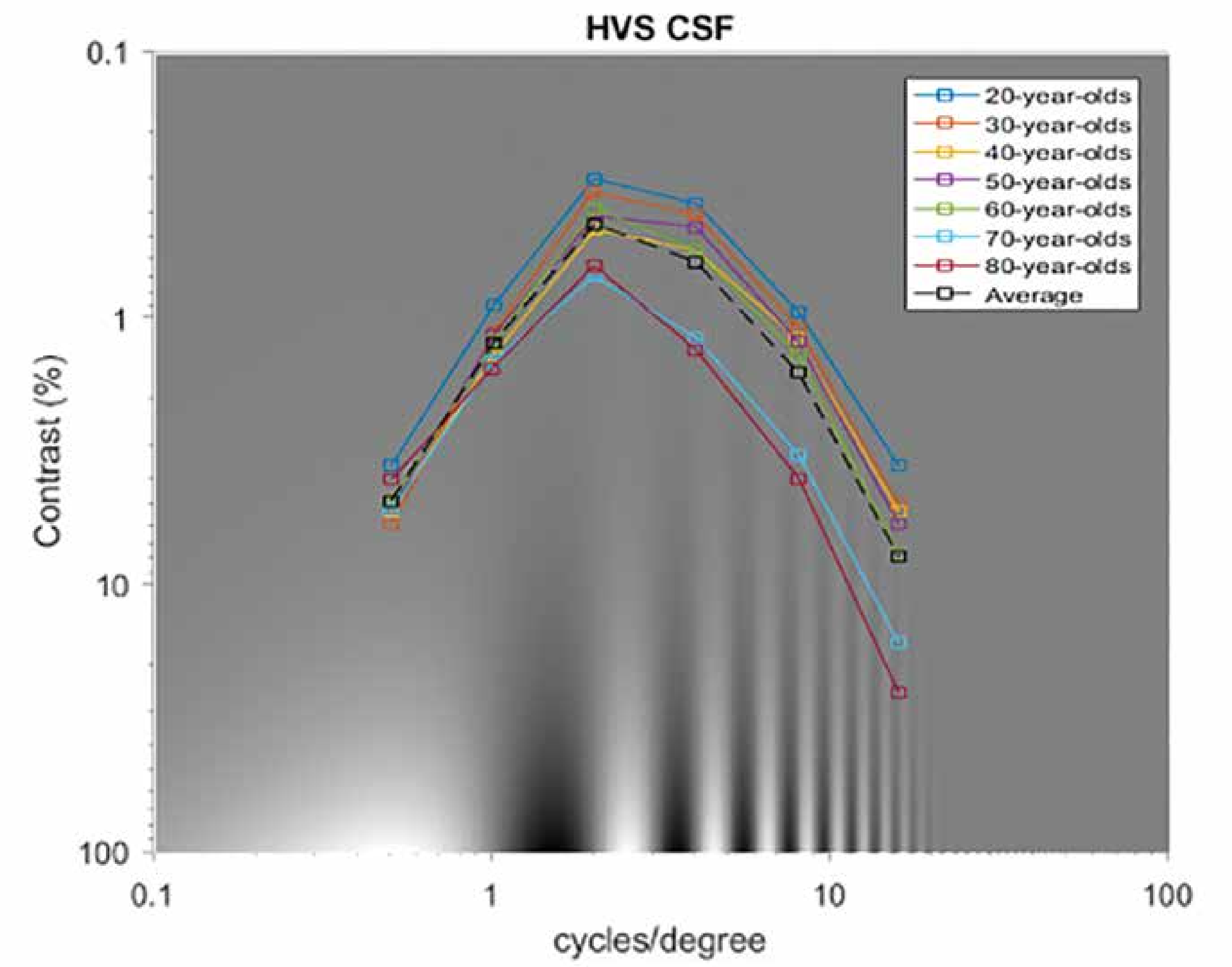

Fig 3: The contrast sensitivity functions of the human visual system by age (after Schieber, 1992) overlaid upon a sine wave of increasing frequency along the x-axis and decreasing contrast along the y-axis.

MTF at the Nyquist frequency is 0 for a $Q = 2$ system and 0.25 for $Q = 1$), resulting in sharper images. Furthermore, because the frequencies above the Nyquist limit are also being modulated, sometimes severely, the aliasing that does occur will also be modulated, diminishing the visibility of those spatial frequencies.

In conclusion, one should make sure they select a range of target sizes for a system to focus on. It may help to make this decision with an understanding of the limitations of the human visual system, especially if the targets are chosen based upon a human interpreting a target. MTF concerns should be considered if extra-fine sampling is determined to be required, as these are the frequencies at which there will be the most aliasing, depending upon the Q design of the system.

3. Resolution and signal level

It is important to consider all implications of higher-resolution imaging systems. It will become apparent that having a sensor with the largest number of pixels is not necessarily most appropriate for a particular situation. A significant portion of this discussion is again based upon the concept of GSD. Smaller pixels in a sensor will measure fewer photons in the same exposure time, thus decreasing the signal-to-noise ratio (SNR). Because doubling the resolution of a detector halves both the x- and y-direction of the pixel pitch, the area of a given pixel to capture photons is reduced to one quarter. Because this also reduces shot noise of the measurement by the square root of the signal, the SNR is reduced in proportion to the increase in linear spatial resolution, and is written as

[6] Schieber 1992.

$$SNR = \frac{N_{sig}}{\sigma_{sys}} = \frac{N_{sig}}{\sqrt{N_{sig}}} = \sqrt{N_{sig}} \quad , \tag{6}$$

where N_{sig} is the signal level (number of electrons, photons, digital counts, etc.), and σ_{sys} is the shot noise of the system.

3.1 Integration time and total power

The decrease in signal due to smaller pixels may be addressed in two ways. The strength of the measured signal could be increased by increasing some combination of the integration time and the amount of light incident upon the target. Increasing integration time is simpler with static detectors, as dynamic systems will have an increase of pixel smear and jitter, which will impact the MTFs. One important concern for cultural heritage documents is that both methods increase the total amount of energy received by the imaging system, but also increase the total energy on the target. These objects usually are sensitive to incident radiation and under various control standards. Documents, inks, and pigments can be damaged by incident light either by chemical reaction or by heating of the target. The British Standards Institution has a standard for recommended lighting of cultural collections, *PAS198:2012 Specification for Managing Environmental Conditions for Cultural Collections*. This standard recommends a document regularly displayed be limited to 50 lux (lumen/m^2). Andrew Beeby (2018) states that typical conservation imaging setups use approximately 1000 lux over a much shorter period.[7] This results in 8000 lux-hr being achievable over a month of exhibition time or a day of conservation imaging.

3.2 Well depth

Because improved resolution decreases the pixel area, and therefore the number of photon-generated electrons that can be measured by a pixel before writing out the data. This maximum number of photoelectrons is known as the 'well depth'. This constraint to the number of possible detected photoelectrons constrains the possible signal-to-noise ratio of the image, which increases as the square root of the number of detected photons, as shown in Eq. (5). Therefore, larger well depth allows for more discrimination in the signal measured as well as allowing more signal to be collected compared to the detector inherent noise level, further increasing the SNR

[7] Beeby et al. 2018.

3.3 Contrast sensitivity function

Recent research has highlighted considerations of the contrast sensitivity function (CSF) with respect to minimum detectable thresholds for both targets (overtext and undertext) and noise in an image.[8] The CSF can be seen in Figure 3, with a CSF curve overlaid on a frequency and contrast varying signal to highlight the region of detection for the HVS. At high frequencies, change detection is reduced by diffraction, chromatic aberration, and spherical aberration within the eye itself. Low frequency detection is reduced due to neural processing optimized for a high pass filter to detect fine details.

Therefore, signal should be considered based on target size, especially for large values of spatial frequency. Just because the detector measures a difference in signal does not mean that the human visual system will be able to discern it. The target will only be discernable if, dependent upon the resolution, the contrast between the target and background is of a significant relative magnitude. Methods like principal component analysis and spectral angle mapper may be used to increase the contrast between the target (text) and background (parchment). SNR should be maximized to limit the impact of shot noise (noise based on variability of the signal) on the system, particularly when image processing steps may attempt to histogram stretch an image for better visualization. This is a method that increases contrast of all aspects of the image, including noise.

In conclusion, the optimal resolution will have to be balanced between fine enough to be appealing and usable by human analysts, yet coarse enough to allow quick signal gathering to prevent light damage to targets, which will also increase the SNR for image processing algorithms. The human usability could also be enhanced using panchromatic sharpening, which mathematically blends the spatial and spectral resolution of two images into one higher resolution image.

4. Imaging system modeling

Because there are many options when designing an imaging system, and investing in a new one can be expensive, it may be beneficial to attempt to model systems before acquiring them. This methodology is based off radiometry, which follows photons through a well-defined scene, described by a light source, a reflectance target, and an imaging system.

[8] Peery and Messinger 2018.

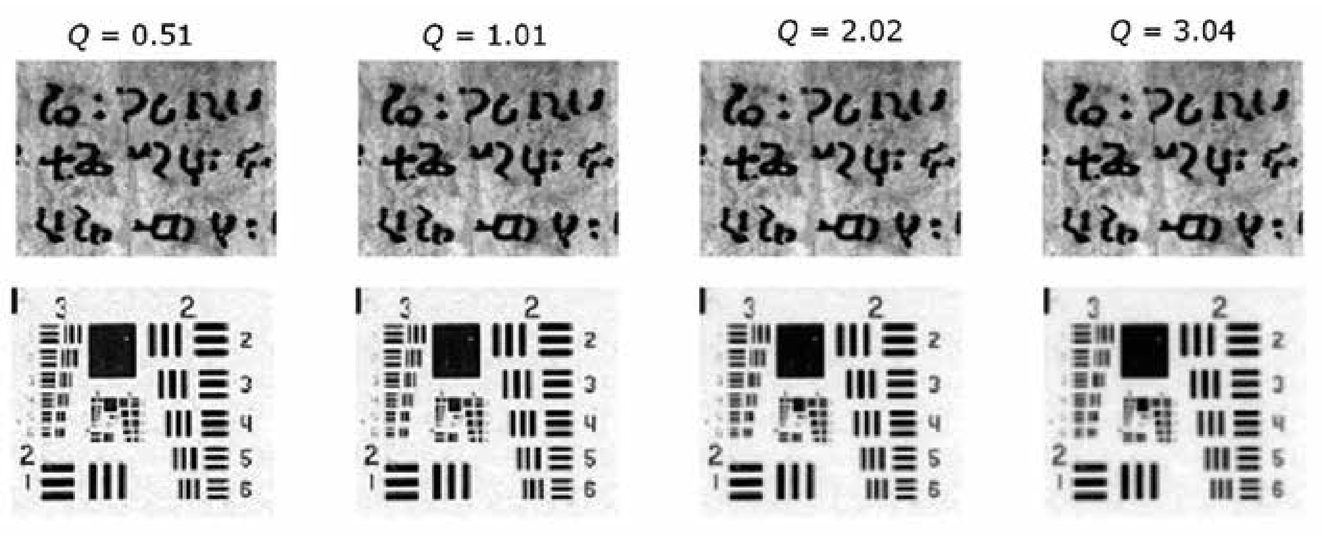

Fig 4: Effects of *Q* on image sharpness. Images with smaller values of *Q* appear sharper as the amplitudes at large spatial frequencies are increased, but this can also exhibit aliasing. Depending on the *Q* value and the frequencies of the image, this may be indiscernible.

The basic idea is to use a high-fidelity image taken with one system, and then modeling an expected output from another system, by tracking pertinent variables.

4.1 Modulation transfer function (MTF)

The modulation transfer function (MTF) of the system was modeled by combining the MTFs of the optics, wavefront error, system jitter, pixel smear, and pixel pitch as

$$MTF_{sys} = MTF_{optics}\ MTF_{sensor} \cdot MTF_{jitter} \cdot MTF_{smear} \cdot MTF_{pitch} \cdot \qquad (7)$$

These quantities are specified in accordance to Fiete's system model used for remote sensing[9]

$$MTF_{optics} = \frac{2 \cdot (A+B+C)}{\pi\left(1-\varepsilon^2\right)} \quad . \qquad (8)$$

Though the smear and jitter values may be negligible for a stationary framing camera, added motion from a scanning system would most likely increase these.

The system MTF can now be plotted with respect to the pixel size of a system and thus its Nyquist frequency. By varying the aperture size, and thus adjusting MTFsys, different values of Q can be compared with respect to aliasing, as shown in Figure 2.

4.2 Sampling

Modeling images to view the different impacts of Q required modeling the basic Fourier process of image capture. This includes convolving the original input image, $f(x, y)$ with the point spread function of the system (the inverse 2-D Fourier transform of the MTF H(ξ, η)), and then multiplying by the sampling function $s[x,y]$. This can also be done in the frequency domain by evaluating the Fourier transform of the image and multiplying by the MTF, as

$$g[x,y] = \left(f[x,y] * h[x,y]\right) \cdot s[x,y] \qquad (9)$$

where '*' denotes the mathematical operation of convolution.[10]

This downsampling process allowed aliasing to be investigated from an existing image. Adjusting MTF alone could not produce new aliasing, as the image had already been sampled by some detector, whether it was a historic document imager, conventional scanner, or any computer generated image (with pixels as the sampling function). As the image was already 'captured' once, all frequencies above the relevant Nyquist frequency have been removed. No MTF adjustment could enhance the frequencies beyond ρ_{Nyq}, as they no longer existed. By downsampling, ρnyq was reduced by increasing the effective pixel spacing according to Equation 6. Various MTFs could then be applied, enhancing or limiting frequencies that reach the sampling function. If the MTF were to cutoff frequencies above the new ρ_{Nyq} then no aliasing would exist.

[9] For full details, including Eq 8 variable values, see Fiete 2002.

[10] Easton 2010.

Table 2: Proposed cultural heritage relevant targets at theoretical NIIRS levels and their associated approximate sizes.

N	Example	Linear Dimension	Average	Ratio (N/(N+1))
7	Large picture (page width)	8.5 in (.215 m)	215 mm	2.11
8	Small Picture (half width+margin)	4 in (.102m)	102 mm	4.86
9	Word of text	5 letters = 5x below ~5/6 = .02 m	21 mm	5.00
10	Character of text	72 pts/in, 12 pt = 1/6 in = .004	4.2 mm	5.60
11	Pen stroke	0.1-1.4 mm fountain pens	0.75 mm	3.95
12	Overlapping strokes	¼ of pen stroke, .025–.35 m	0.19 mm	1.92
13	Hairs breadth	17–181 um (.181–.017 mm)	0.099 mm	2.20
14	Fingerprint	500–590 dpi (.05 –.04 mm)	0.045 mm	**Ratio Avg = 3.66**

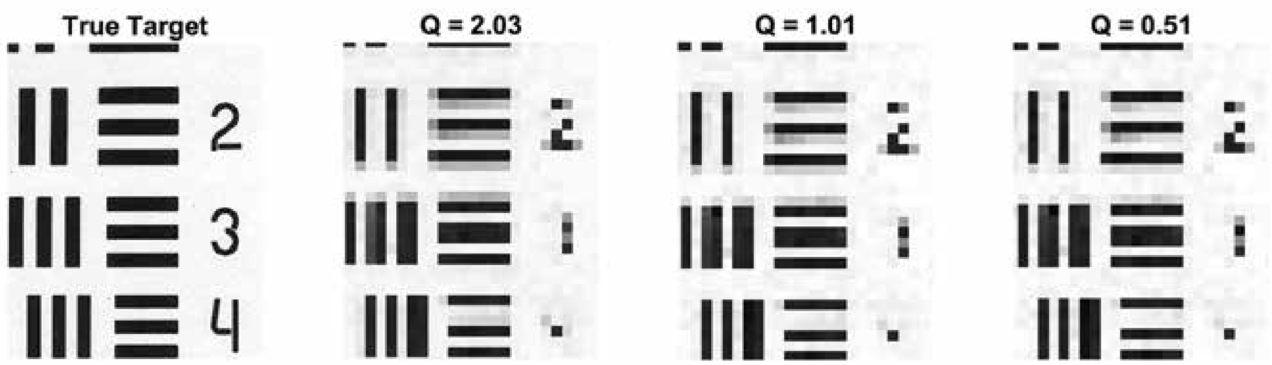

Fig 5: Aliasing can be seen at various Q values, increasing as Q decreases to the right. The true target was blurred by the MTFs of Figure 2. The sampling size was selected for the horizontal bars around line 3 to be at ρ_{nyq}. Aliasing is most visible on the horizontal bars of target 2, as well as making out the numerals 2–4 in higher Q's and being unable to do so at lower Q.

5. Analysis

A list of proposed NIIRS values, their example targets, typical size, and ratio to following levels is shown in Table 2. The scaling ratio of approximately 2x GSD per NIIRS level was followed, per Harrington, et al. (2015). The ratio of GSD's in the final column of Table 1 and 2 can be compared to see relative similarity in scaling, with large uncertainty on some levels due to ambiguity of target definition.

The impacts of the modulation transfer function (MTF) on image quality is yet another engineering balancing act. The MTF of a system defines how different wavelengths of

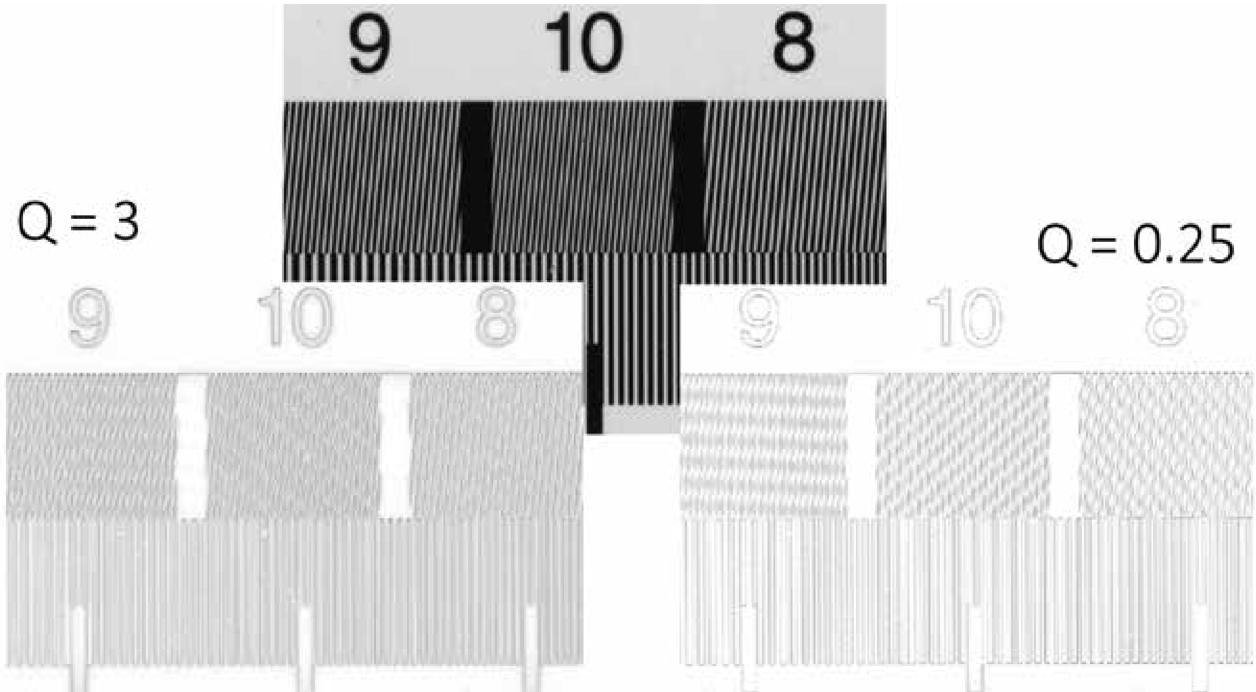

Fig 6: Other options for showing aliasing. Aliasing is highlighted in difference images (bottom) as new patterns. The original image (top) is composed of bars at approximately a 15-degree angle at discrete frequencies, and a lower bar of vertical bars regularly increasing in frequency. Aliasing can be seen in $Q = 0.25$ (right) as horizontal bars in window 9, 45 degree bars in 10, and crossing bars in window 8. Aliasing in the lower bar is highlighted as irregular intervals. $Q = 3$ (left) only shows differences based on blurring and modulation of existing frequencies.

light are modulated through the imaging system, defined primarily by the aperture of the lens and the pitch of the pixels, as seen in Equation 8. Because the MTF describes which frequencies, and how much of said frequencies, get through a system, they can be used to determine two important characteristics: how sharp an image is (based on how many high frequencies are passed) and how much aliasing is occurring (based on how many frequencies past the Nyquist frequency enter the system).

The impacts of this aliasing, based on the Q of a system, can be seen in Figure 5. The aliasing effect can most clearly be seen in the horizontal bars of the resolution targets. Sharpness in an image will not only affect human perception, but also computer algorithms. Different algorithms can be affected differently by sharpness,[11,12] therefore pertinent ones should be investigated when designing a system. Most optical systems tend to design to Q = 0.5-1.5, catering to sharper images for the human visual system.[13] The impacts of aliasing on expected uses for the system should also be investigated, to decide whether a lower Q would be acceptable or not. For reference, the Q of the MSI system modeled in this project is approximately 0.5.

Figure 4 was analyzed for CSF calculations based upon overtext, undertext, and shot noise (pixel size). These resolutions were determined based upon the imaging GSD as well as display assumptions, based on a viewing distance of 22.5 in.[14] The results of the target and noise analysis can be reviewed in Figure 9. This shows the overtext and some undertext should indeed be the most discernable, shot noise within the background of the parchment is potentially visible for those with high visual acuity, and noise within the text is not visible.

An analysis of the HVS CSF with regard to the target texts and noise from Figure 7 can be seen in Figure 9. The resolutions were based upon the size of a pixel on a computer display and how many pixels made up a target (pen stroke on a character of text) or noise (a single pixel for Poisson photon arrival statistics). The contrast was measured based on the mean value of the target or signal,

[11] Webster, Anthony, and Scheirer 2018.

[12] Peery and Messinger 2018 (10644).

[13] Fiete 2010.

[14] An in-depth description of the analysis can be seen in Peery and Messinger 2018, where the noise was analyzed based on Poisson arrival statistics of the photons.

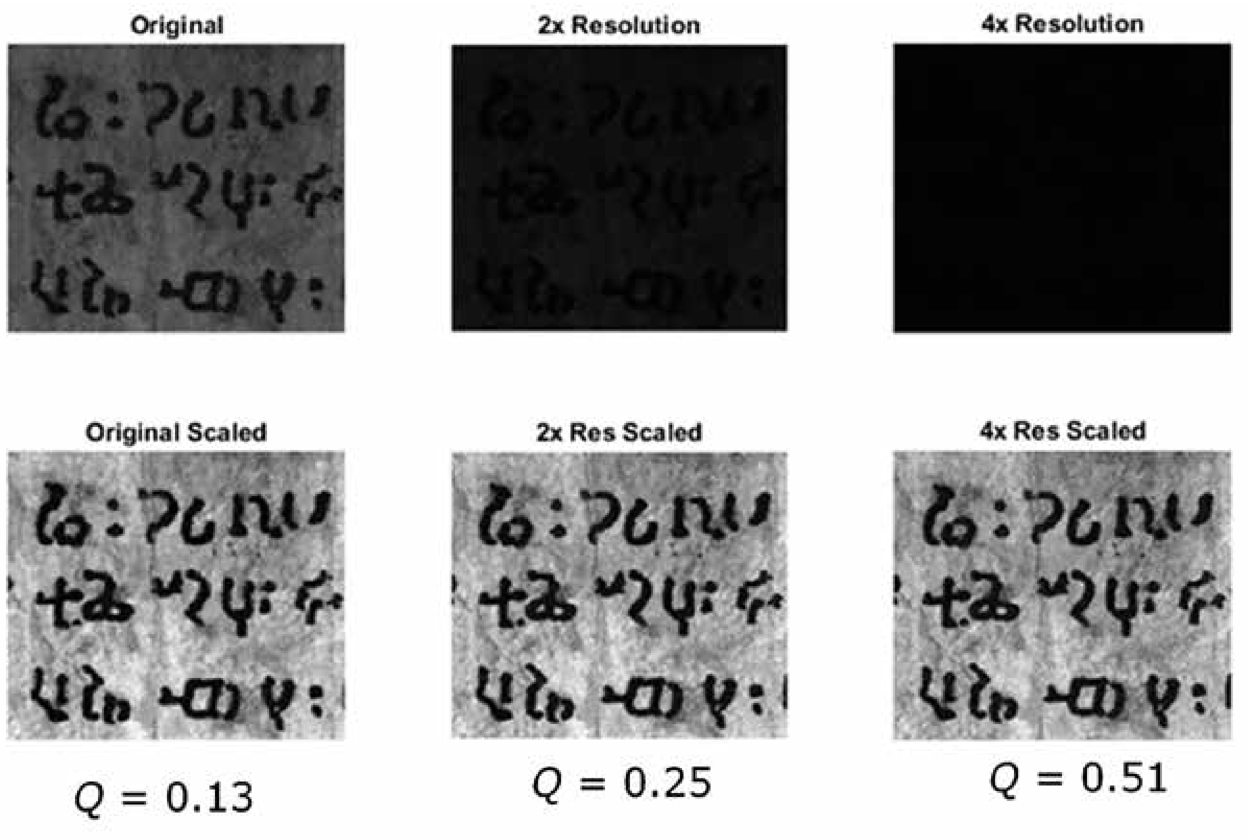

Fig 7: Effect of decreasing pixel size: spatial resolution increases linearly, while sensor area decreases exponentially. Constant scaling is maintained across the top row of images based upon the well depth of the system. The lower images are replicas that have been stretched to use the full dynamic range of the system, but also that highlight the reduced SNR of systems with higher Q.

compared with the mean of the background. For the overtext and undertext, this is a relatively straightforward measurement. For the noise levels, the background was either the mean of the parchment or the mean of the text, and the signal noise was based on the variance of the signal based upon shot noise parameters for that mean signal level.

If all other aspects of the system are considered equal, one should also consider the increase in memory required for larger resolution files. Increasing the resolution (decreasing sample size) by a factor of two will increase both the write time and the required amount of storage by the square of the increase, due to having to increase in two dimensions. File size is already a concern of high resolution imaging and combining that with hyperspectral images would only compound the issue further. If storage space for images is a concern, this should be considered by the user.

6. Conclusions

In conclusion, if higher resolution is not required for one's targets of interest, it will cost additional time to maintain the same signal to noise ratio and will also require additional storage space exponentially proportional to the resolution increase. To determine if a target of interest requires higher resolution, NIIRS examples such as the ones listed in Table 2 should be referenced. If the targets were made for human interpretation, human vision system limits should be considered with this. If a higher resolution is required, aliasing could negatively impact higher frequency sampling and should be considered by the Q factor of a system. Signal costs can be offset with increases to integration time, but this needs to be weighed against time constraints of the data collect as well as total power limitations on potentially fragile targets. A recap of the costs, benefits, and their respective caveats can be reviewed below:

Fig 8: The same type of modeling as Figure 7, but over a flat response reflectance target to highlight the 'salt and pepper' noise added to the system due to lower SNR values at higher resolution.

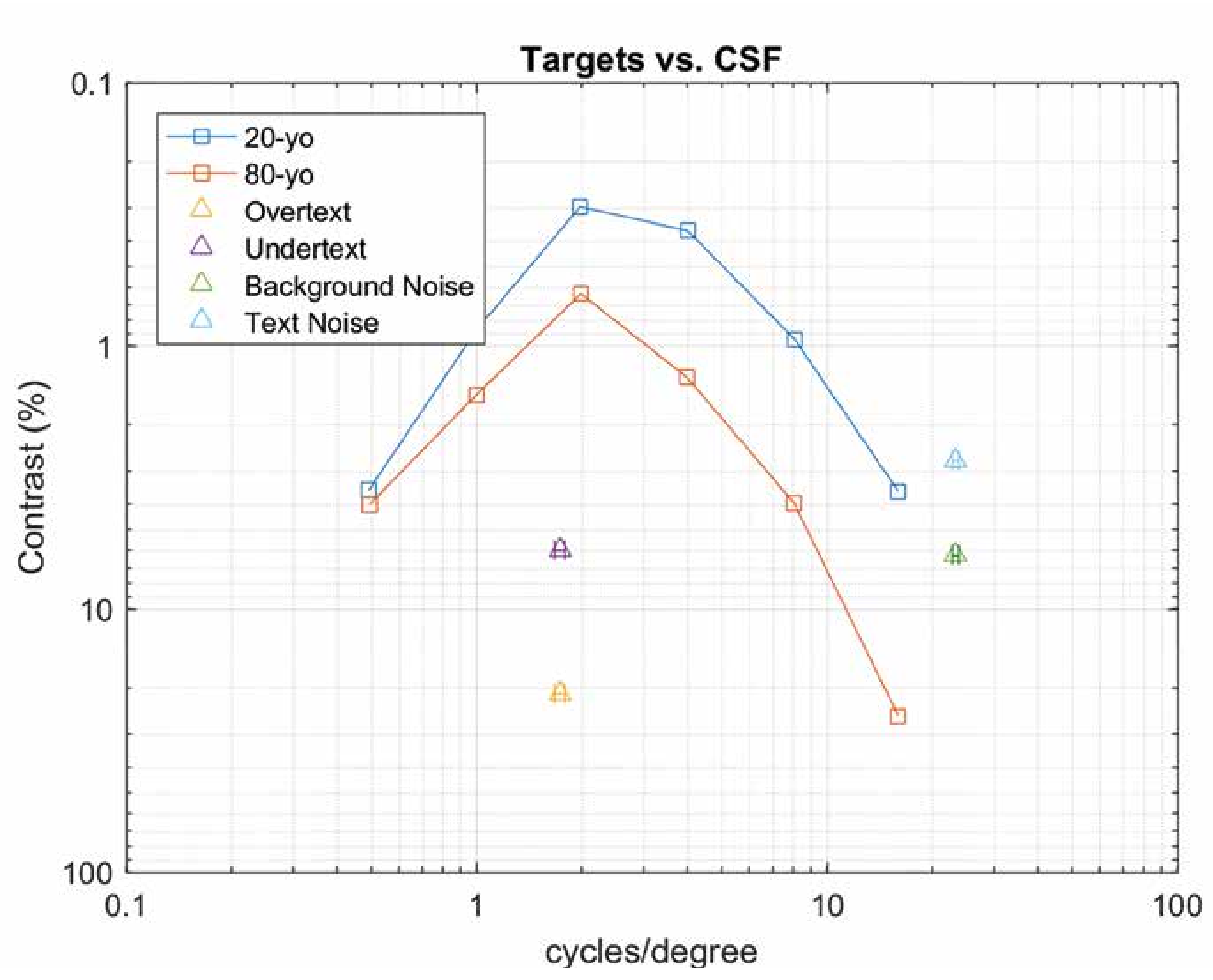

Fig 9: The two limiting CSFs plotted with the resolution and contrast values of overtext, undertext, background noise, and text noise measured at the scale of Figure 7 with a full well depth at 80% reflectance of the R-CHIVE system.[15]

- Benefits of Higher Resolution:
  - Finer detail may be seen in the data (assuming it is present and detectable)
    - Consider Q aliasing at finer resolutions
    - Consider HVS limitations for pertinent target levels
  - Potentially sharper images
- Costs of Higher Resolution:
  - Reduction in signal-to-noise ratio (SNR)
    - May require longer integration time or increased signal to counter
    - Consider time/energy constraints on sensitive targets
  - Additional memory requirements for writing/storage

7. Future Work

The General Image Quality Equation (GIQE) has undergone several revisions, leading to the latest GIQE 5. These changes switched the image being evaluated to the unenhanced image, as opposed to one that has undergone image processing techniques to enhance usability. This allows for a master image to be defined on its image quality, and any individual's image processing techniques could be applied to that base. The latest equation relies upon the GSD, signal-to-noise ratio (SNR), and the relative edge response (RER), which defines the sharpness of the image. Given these parameters, a NIIRS value can be output for a given image without requiring specialized analysts to evaluate each image to assign a value they deem appropriate.[16]

A general image quality equation could be developed for cultural heritage targets similar to those proposed in Table 2, such that curators would know what type of system specifications would be required to achieve their imaging goals, based upon target resolution.

[15] Plot taken from Peery and Messinger 2018.

[16] For latest version, see Harrington et al. 2015.

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Written Artefacts as Cultural Heritage

Ed. by Michael Friedrich and Doreen Schröter

Written Artefacts as Cultural Heritage was established in 2020. The series is dedicated to the double role of written artefacts as representations and generators of humankind's cultural heritage. Its thematic scope embraces aspects of preservation, the identity-defining role of artefacts as well as ethical questions.

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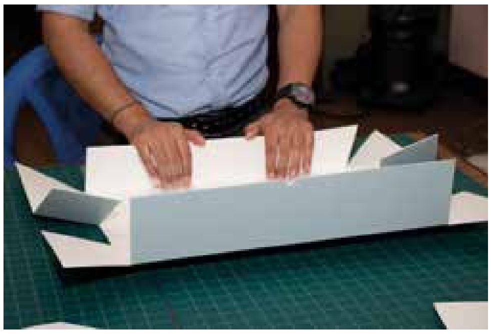

manuscript cultures (mc)

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manuscript cultures encourages comparative approaches, without regional, linguistic, temporal or other limitations on the objects studied; it contributes to a larger historical and systematic survey of the role of written artefacts in ancient and modern cultures, and in so doing provides a new foundation for ongoing discussions in cultural studies.

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manuscript cultures 14

manuscript cultures 13

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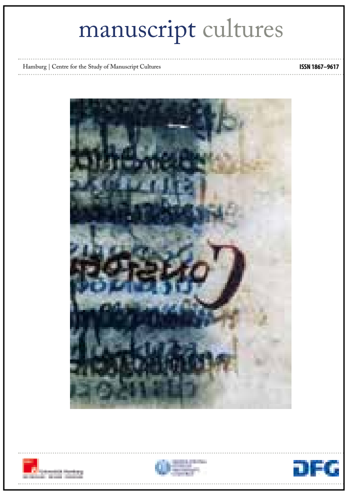

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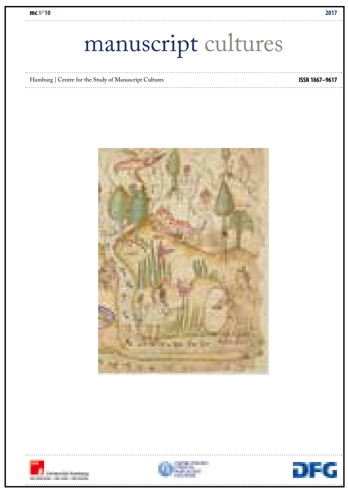

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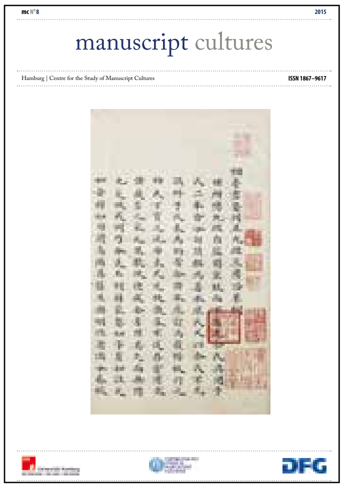

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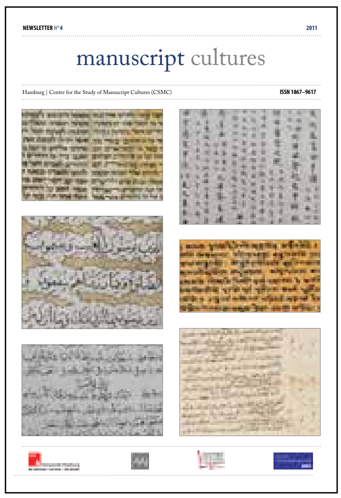

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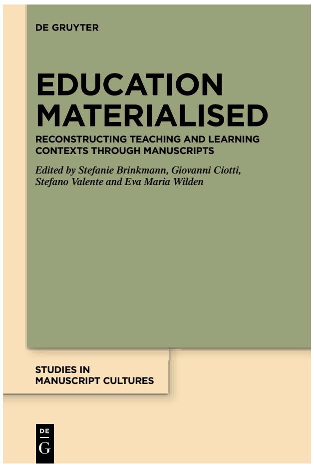

23 – *Education Materialised: Reconstructing Teaching and Learning Contexts through Manuscripts,* edited by Stefanie Brinkmann, Giovanni Ciotti, Stefano Valente and Eva Maria Wilden

Manuscripts have played a crucial role in the educational practices of virtually all cultures that have a history of using them. As learning and teaching tools, manuscripts become primary witnesses for reconstructing and studying didactic and research activities and methodologies from elementary levels to the most advanced.
The present volume investigates the relation between manuscripts and educational practices focusing on four particular research topics: educational settings: teachers, students and their manuscripts; organising knowledge: syllabi; exegetical practices: annotations; modifying tradition: adaptations.
The volume offers a number of case studies stretching across geophysical boundaries from Western Europe to South-East Asia, with a time span ranging from the second millennium BCE to the twentieth century CE.

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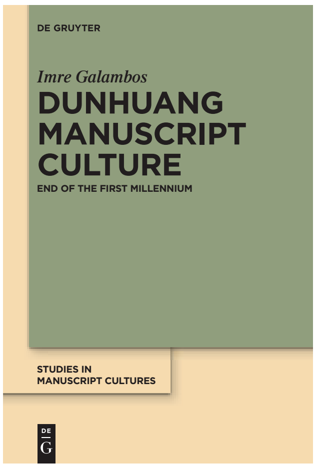

22 – *Dunhuang Manuscript Culture: End of the First Millennium*, by Imre Galambos

Dunhuang Manuscript Culture explores the world of Chinese manuscripts from ninth–tenth century Dunhuang, an oasis city along the network of pre-modern routes known today collectively as the Silk Roads. The manuscripts have been discovered in 1900 in a sealed-off side-chamber of a Buddhist cave temple, where they had lain undisturbed for for almost nine hundred years. The discovery comprised tens of thousands of texts, written in over twenty different languages and scripts, including Chinese, Tibetan, Old Uighur, Khotanese, Sogdian and Sanskrit. This study centres around four groups of manuscripts from the mid-ninth to the late tenth centuries, a period when the region was an independent kingdom ruled by local families. The central argument is that the manuscripts attest to the unique cultural diversity of the region during this period, exhibiting – alongside obvious Chinese elements – the heavy influence of Central Asian cultures. As a result, it was much less 'Chinese' than commonly portrayed in modern scholarship. The book makes a contribution to the study of cultural and linguistic interaction along the Silk Roads.

Studies in Manuscript Cultures (SMC)

Ed. by Michael Friedrich, Harunaga Isaacson, and Jörg B. Quenzer

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21 – *Disiecta Membra Musicae: Studies in Musical Fragmentology*, edited by Giovanni Varelli

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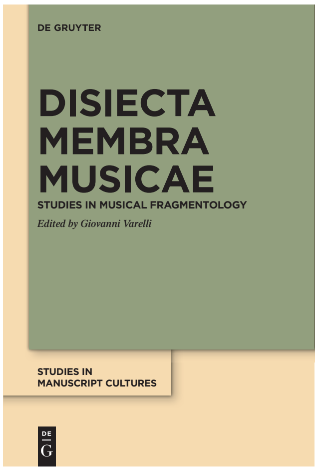

Although fragments from music manuscripts have occupied a place of considerable importance since the very early days of modern musicology, a collective, up-to-date, and comprehensive discussion of the various techniques and approaches for their study was lacking. On-line resources have also become increasingly crucial for the identification, study, and textual/musical reconstruction of fragmentary sources. *Disiecta Membra Musicae. Studies in Musical Fragmentology* aims at reviewing the state of the art in the study of medieval music fragments in Europe, the variety of methodologies for studying the repertory and its transmission, musical palaeography, codicology, liturgy, historical and cultural contexts, etc. This collection of essays provides an opportunity to reflect also on broader issues, such as the role of fragments in last century's musicology, how fragmentary material shaped our conception of the written transmission of early European music, and how new fragments are being discovered in the digital age. Known fragments and new technology, new discoveries and traditional methodology alternate in this collection of essays, whose topics range from plainchant to *ars nova* and fifteenth- to sixteenth-century polyphony.

20 – *Fakes and Forgeries of Written Artefacts from Ancient Mesopotamia to Modern China,* edited by Cécile Michel and Michael Friedrich

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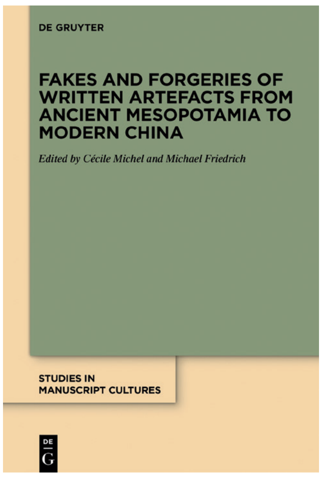

Fakes and forgeries are objects of fascination. This volume contains a serie of thirteen articles devoted to fakes and forgeries of written artefacts from th beginnings of writing in Mesopotamia to modern China. The studies empha sise the subtle distinctions conveyed by an established vocabulary relating t the reproduction of ancient artefacts and production of artefacts claiming t be ancient: from copies, replicas and imitations to fakes and forgeries. Fake are often a response to a demand from the public or scholarly milieu, or eve both. The motives behind their production may be economic, political, reli gious or personal – aspiring to fame or simply playing a joke. Fakes may be revealed by combining the study of their contents, codicological, epigraphi and palaeographic analyses, and scientific investigations. However, certain fa mous unsolved cases still continue to defy technology today, no matter how advanced it is. Nowadays, one can find fakes in museums and private collec tions alike; they abound on the antique market, mixed with real artefacts tha have often been looted. The scientific community's attitude to such objects calls for ethical reflection.

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