Signal-to-Noise Ratios in \textit{IUE} Low-Dispersion Spectra. II. Photometrically Corrected Images

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ABSTRACT. The character of detector noise is explored in photometrically corrected images from the short-wavelength and long-wavelength prime intensified vidicon cameras of the \textit{International Ultraviolet Explorer}. A protocol is proposed for deriving realistic "noise models"—crucial to the application of Optimal extraction algorithms like that of Kinney, Bohlin, and Neill (1991, \textit{PASP}, 103, 694)—from the available collections of UV-Flood calibration images. The protocol includes evaluation of the "noise-filtering" properties of the SWP and LWP cameras through 2-D spatial power spectrum analysis. The two vidicon cameras behave nearly identically. For both, the incomplete removal of the pixel-to-pixel sensitivity pattern can lead to a factor of up to two enhancement in the apparent noise, depending on position in the image. Even with good suppression of the pixel granularity, however, the remaining random noise can exhibit saturation behavior that causes the S/N to cease improving with increasing exposure. The random noise itself exhibits a two-component character: a normal white-noise field superimposed on a filtered (Gaussian-like smoothing) background. The influence of the smooth component varies strongly with position. Nevertheless, when all of the relevant effects are considered, the underlying "pristine" noise models show essentially no dependence on spatial position, except for an unusually noisy patch on the LWP camera. Two additional sources of noise, beyond the largely photometric contributions documented above, are microphonics and cosmic particle radiation. Microphonics are important in only a few exceptional circumstances, but cosmic ray "bright spots" set an effective limit of \( \approx 4 \) hr on useful SWP-LO exposures of (unresolved) emission-line objects, even those conducted during low-radiation time.

1. INTRODUCTION

The first paper of this series (Ayres 1990; hereafter referred to as Paper I) discussed the signal-to-noise properties of the short-wavelength prime (SWP) detector\(^1\) of the \textit{International Ultraviolet Explorer}. The discussion focused on an analysis of flatfield images obtained during an extensive calibration of the camera in early 1985. My motivation was to provide a quantitative way to estimate SWP-LO integration times to achieve target S/N levels in far-UV spectra of chromospheric emission-line stars. I concluded that the successful removal of the pixel-to-pixel sensitivity (the "granularity") of the vidicon images held the key to achieving maximum S/N. Owing to a technical detail, the present version of the \textit{IUE} Spectral Image Processing System (\textit{IUESIPS}) only partially removes the granularity, particularly in the regions of the camera format where the resolution is highest (corresponding to \( \lambda < 1500 \) \AA{} in the low-dispersion SWP spectrum). As a result, production-processed \textit{IUE} spectra are noisier than they should be.

In the present paper, I demonstrate several realizations of photometric correction procedures and their influence on the derived S/N of \textit{IUE} images. I use these techniques to explore the fundamental nature of noise in the two operational cameras of the \textit{IUE} (SWP and LWP). I illustrate the magnitude of improvements to be expected with the new version of the production system ("\textit{NEWSIPS}") which the \textit{IUE} Project is using to reprocess the historical collection of spectrograms for its Final Archive (Nichols-Bohlin 1992). I also show how to derive position-dependent "noise models" which are at the heart of "Optimal extraction" algorithms like that developed for \textit{IUE} low-dispersion spectra by Kinney, Bohlin, and Neill (1991; hereafter referred to as KBN). Finally, a companion paper (Ayres et al. 1993; hereafter referred to as ABLB) describes an implementation of an SWP-LO reduction procedure based on these strategies, which I and my colleagues have used in the construction of a large-scale catalog of far-UV fluxes of chromospheric emission-line stars.

2. PHOTOMETRIC LINEARIZATION OF \textit{IUE} IMAGES

2.1 Overview

The photometric correction seeks to assign a linearized intensity to each recorded data number (DN) in the vidicon image. The foundation of the correction is the intensity transfer function (ITF). It is calibrated by exposing the camera to carefully metered mercury pen-ray lamps (monochromatic emission at 2500 \AA{}). A series of graded exposures is designed to cover the full range of output DN,
and several independent flatfields are obtained at each exposure level in order to improve the statistical quality of the pixel-to-pixel granularity.

In the 1985 SWP calibration effort, for example, no fewer than five flatfields were taken at each of twelve independent exposure levels, where the first is the “NULL” background (typically 10–20 DN) that remains on the camera following the preparation cycle. Frequent exposures at the 100% level (182-s exposure: 23 images) were taken to track variations in the output of the UV-Flood lamps over the several day period, and a large number (27) of NULL exposures were acquired as well.

Having obtained an appropriate collection of calibration images, there are several approaches that one might take in constructing and applying the correction function. In the present version of the JUESIPS, the ITF is retained as a set of twelve images, each representing the coaddition of several flatfields at that level. The coaddition was done in a geometrically corrected frame, defined according to a 13×13 grid of reseaux (fiducial marks emplaced in a transfer optic). The geometrically rectified ITF then is mapped back into the raw space of a production science image according to displacement vectors specified as a function of camera temperature. The linearized image is obtained through interpolations in the remapped twelve-level ITF table. The geometrical correction of the original UV-Flood images to construct the ITF, and the subsequent mapping back to raw space to apply it, impose a double smoothing on the ITF levels which suppresses the inherent pixel-to-pixel sensitivity variation. Consequently, the intrinsic granularity of the raw science image partially survives the photometric linearization, and carries through to the corrected image. That is the origin of the enhanced “fixed pattern” noise in JUESIPS-processed images (e.g., Bohlin 1988).

In contrast, the Final Archive NEWSIPS procedure constructs the ITF in raw space, and spatially cross correlates it against a science image to gauge any (slight) local displacements of the latter resulting from short-term thermal distortions of the camera format. The ITF then is mapped onto the (possibly slightly distorted) pixel grid of the target raw image, and the output intensities are obtained by interpolation. The idea is to register the ITF to the fixed pattern of the science image as closely as practically possible, to achieve optimum suppression of the fixed-pattern noise (see Nichols-Bohlin 1992 for details).

However, the cross-correlation registration and spatial interpolation used in NEWSIPS exhibits unsatisfactory properties with regard to analyzing particular components of the random and systematic noise. For example, the errors that result from the photometric linearization itself cannot be assessed straightforwardly: application of the ITF to one of its constituent levels would lead to a perfect correction, and the inference of a negligible noise contribution from that source. One also worries that the chi-square minimization aspects of the sophisticated pattern-matching algorithm might subtly obscure the true noise levels in flatfield images.

Thus, for the present investigation I adopted a simplified strategy to linearize the raw images. It utilizes low-order polynomials to model the dependence of the output DN on input intensity on a pixel-by-pixel basis. Furthermore, because the present discussion focuses primarily on the collection of UV-Flood flatfields obtained during the two ITF campaigns—with thermally stabilized cameras—there is no need to implement a sophisticated fixed-pattern registration strategy.

2.2 Polynomial ITF

The first step in constructing the “polynomial ITF” was to create a table of coadded images analogous to that used in the NEWSIPS strategy. I collected the complete set of raw SWP images from the 1985 ITF campaign, and the LWP images from the earlier campaign in late 1984, from the National Space Sciences Data Center. I visually examined each of the frames for defects like data dropouts or spatially extended cosmic ray "hits." For the present study it was sufficient to linearize representative patches of the 768×768 images. I selected three 64×64 regions of the SWP (and LWP) format at key locations along the low-dispersion spectral strips: Fig. 1 illustrates the geometry. I measured the mean DN levels in the three patches on each of the “tracking” images (i.e., 100%-level exposures for SWP; 80% for LWP), and assigned to the other ITF images a correction factor based on spline interpolations in time (within the same observing shift only) of the mean DN-NULL values of the sample of tracking exposures. The corrections account for the variable output of the UV-Flood lamps over the several-day duration of the ITF campaign. I then chose up to five representative images from each exposure group; coadded them to establish a mean image for that ITF level; and calculated an effective expo-
sure time based on the assigned correction factors. I also adjusted the original exposure times for the discretization of the commanded value in steps of the 0.41-s “ticks” of the Onboard Computer, and the (average) 0.15-s rise time of the high-voltage power supply. Table 1 summarizes the exposure time) for the mean DN in each patch. Figures 2(a) and 2(b), depict the raw counts (sector a) of the flatfields.

I scaled the resulting twelve corrected exposure times (from 0 s [NULL] to 632 s [340%] for SWP) into the range 0-250 to define the linearized intensity scale (“Byted Flux Numbers” or BFN; see Table 1). Figures 3(a) and 3(b) depict reduced ITF tables corresponding to the three reference areas for each camera. Figures 4(a) and 4(b) show the dependence of DN on BFN (or equivalently on exposure time) for the mean DN in each patch.

Finally, I fitted fourth-order polynomials to the apparent BFN versus DN relation at each pixel. The photometric correction function then is represented by a series of 2-D tables of polynomial coefficients, that can be applied straightforwardly to the raw image through simple algebraic operations. In practice, I derived the coefficients as a function of DN—NULL, where the difference was stretched onto a standard scale of 0-250 by reference to the value at which the pixel “saturates.” The latter was defined as the maximum DN at that pixel in the top level of the ITF (e.g., 340% exposure for SWP) or 245 DN, whichever was smaller. While 255 DN represents the maximum value that can be passed to the telemetry stream (video chain saturation), some pixels saturate “early:” their output DN never exceeded a critical value, much less than the telemetry limit, regardless of the length of the UV-Flood exposure. Furthermore, the restriction to DN’s less than 245 eliminates the upward branch of the ITF curves (particularly in sector a) where the conversion from DN to intensity can be
highly nonlinear. I also tested each pixel for anomalously poor sensitivity—for example, those pixels shadowed by reseau marks—and flagged them in a separate array. Figures 5(a) and 5(b) depict the polynomial fitting procedure for the mean DN values of the three reference patches (cf., Fig. 4). The final ITF for each camera consists of the following seven tables: the NULL level, the stretching factor SFAC (to scale DN—NULL onto the uniform interval 0—250), four sets of polynomial coefficients (the polynomials were forced to pass through zero, thereby eliminating the constant term), and the reseau mask. The ITF is applied as follows:

1. Subtract the NULL level, and scale the net Data Numbers, permitting some negative extrapolation to account for variations from the adopted NULL level (here "*" indicates a scalar multiplication of the 2-D tables):

   \[ SCL = SFAC \times (DN - NULL) \times (DN - NULL) > -5 \]

2. Inventory reliable values; flag saturated pixels in mask as zeros:

   \[ MASK = (SCL \times LT 250) \]

3. Apply the fourth-order polynomials:

   \[ BFN = SCL \times (POLY1 + SCL \times (POLY2 + SCL \times (POLY3 + SCL \times POLY4))) \]

4. Restrict negative extrapolations to linear coefficient:

   \[ BFN = BFN \times (SCL \times GE 0) + (SCL \times POLY1) \times (SCL \times LT 0) \]

Thus, the tedious linear interpolations through large tables are replaced by simple algebraic operations, at the expense of the initial computation of the polynomial coefficients. However, the latter is entirely negligible.

3. EVALUATION OF NOISE LEVELS IN FLATFIELD IMAGES

3.1 Raw Images

While the present work focuses on photometrically corrected IUE images, it is useful to review some of the results obtained in Paper I (as well as to extend the raw-image analysis to the LWP camera). For that purpose, I measured the average noise levels in the 60 raw images that ultimately constitute the twelve ITF levels of each camera. I determined the granularity (i.e., the systematic component of the pixel-to-pixel sensitivity variation) by measuring the rms deviation of the DN values in the coadded image representing the particular ITF level. The summation of the five individual images suppresses the random components of any noise sources, and emphasizes the sys-
Fig. 4—Average DN levels of the 64 x 64 reference patches of the two ITFs as functions of linearized intensity (proportional to the original exposure times adjusted for the variable UV lamp output). Error bars (where visible) indicate the standard deviation of the mean DN values of the images (typically five) that comprise each merged level, indicating the range of effective exposure due to the variable lamp output. Ideally, the conversion between input intensity and output DN would be strictly linear, and indeed all of the ITF curves are relatively linear at low intensities. However, at higher intensities the sector \( \gamma \) curves are truncated by telemetry saturation (255 DN = 8-bit data word limit), while the sector \( \alpha \) and \( \beta \) curves exhibit noticeable curvature prior to the telemetry cutoff. The nonlinear response in the upper range of DN is due to physical saturation of the camera target. Notice also that the curves are quantitatively similar between the short-wavelength and long-wavelength cameras; not surprising since the two detectors are essentially identical in design and both are calibrated with reference light of the same wavelength.

I subtracted the mean intensity of each image prior to assessing the set-wise rms in order to minimize the influence of the small variations in effective exposure (due to variable lamp output). I determined the rms's by expressing the intensity values as histograms and fitting a least-squares Gaussian to the resulting profile. The approach emphasizes the nearly Gaussian cores of the noise distributions. However, some of the image positions—particularly sector \( \alpha \) of the LWP camera—show clear evidence of non-Gaussian “wings.” In all cases, I restricted the evaluations to a 50 pixel diameter circle centered in each of the three 64 x 64 reference patches.

Figures 6(a) and 6(b) illustrate the random, systematic, and total rms components in the raw images of the two cameras: in essence, primitive noise models. Note that the granularity dominates the random noise at all positions. Also note that sector \( \gamma \) in both SWP and LWP appears to be smoother than the other two areas, while position \( \alpha \) shows the largest granularity, particularly in LWP. In fact, the raw-image noise models are nearly identical between SWP and LWP in sectors \( \beta \) and \( \gamma \), but differ significantly at position \( \alpha \). The similarity of the noise models is not surprising, given that the cameras are essentially identical in design, and are calibrated at the same source wavelength (namely the 2500 Å mercury lamp emission). The enhanced noise at position \( \alpha \) is an anomaly of the LWP that has been known since laboratory qualification of the flight cameras.

The upper branches of the raw-image noise models indicate the (high) degree of apparent noise that one will...
obtain if the photometric correction does not successfully remove the fixed pattern of the pixel-to-pixel sensitivities. The lower branches indicate the minimum noise levels that can be attained with complete removal of the fixed pattern.

Previously (Paper I), I showed that the variation of the empirical rms’s with DN could be modeled simply as $\sigma_{DN} \sim \sqrt{DN} - \text{NULL}$; the curves through the uppermost and lowermost values in Fig. 6 represent such fits. In subsequent diagrams, I will compare the empirical noise derived from the raw images with the apparent noise levels in photometrically corrected images, processed through a variety of realizations of linearization functions. The $\sigma_{DN}$ can be converted to the equivalent $\sigma_{BFN}$ by multiplying by the gradient of the ITF evaluated at the reference DN value.

3.2 Photometrically Corrected Images

In order to illustrate the influence of the ITF on the apparent noise levels in photometrically corrected images, I derived three polynomial ITFs representing different strategies that one might adopt in practice. The first ITF—phot—was calculated in the reference frame of the raw images with no manipulation of the merged ITF levels. The phot ITF mimics an ideal linearization for those images (e.g., from the ITF campaign itself) that are essentially unshifted with respect to the fixed patterns of the ITF levels. The second ITF—smooth—was derived also in the raw-image frame, but the ITF levels each were rotated by $+45^\circ$ followed by the inverse rotation prior to fitting the polynomials. The double rotation acts as a mild smoothing and is intended to simulate the ITFs currently used in the IUESIPS. The third ITF—rotd—was derived in a rotated reference frame, where the rotation angle ($139.2^\circ$ for SWP, and $139.9^\circ$ for LWP) places the low-dispersion spectrum parallel to the image SAMPLE axis: in essence, the simplest useful geometrical manipulation. The rotd ITF is intended to be applied to a raw image that has been identically rotated, so that the fixed pattern suffers a similar degree of smoothing both in the ITF and in the image to be corrected. As a key part of the rotd procedure, the photometrically corrected image is spatially smoothed with a 1.5 pixel FWHM (2-D) Gaussian to suppress high-frequency noise resulting from subpixel misregistrations, without compromising the effective resolution of the science image.

The rotd ITF represents an alternative strategy to that adopted by the IUE Project to suppress misregistration noise. The Project philosophy, derived from the work of Linde and Dravins (1988) with the LWR camera, is to register the ITF and science image by cross correlating representative patches of the latter with the corresponding intensity levels of the former. The procedure implicitly assumes that the granularity of the images does not change character with the subpixel thermal shifts. If the fixed pattern does change significantly with the thermal shifts, then one should have a separate ITF for each identifiable shift: a daunting prospect from a calibration standpoint. On the other hand, if the structure of the granularity remains the same, but simply is displaced, then prior smoothing of both the ITF and science image should be effective in suppressing the “misregistration” noise, possibly as effective as the cross-correlation technique. Indeed, in the latter one must manipulate either the science image or the ITF at the application stage if a non-negligible shift is obtained, and any manipulation will lead to smoothing of the fixed pattern that one desires to remove.

Figures 7(a) and 7(b) depict empirical noise models for the phot ITF analogous to those displayed previously for the raw images. The extremes of the raw-image noise models are illustrated, scaled to BFN units, as the shaded envelopes. Again, the uppermost points (large squares) for each sector indicate the spatial rms averaged over the set of flatfield images at each ITF exposure level; small squares indicate the spatial rms in the photometrically corrected merged ITF level itself; and circles indicate the average set-wise rms among the (up to) five images at each ITF exposure level. The latter represents the random noise component among the ITF images, and is comfortably close to the lower envelope of the scaled raw-image noise. The spatial rms in the ITF level itself represents a (minimal estimate of) the noise associated with the photometric correction procedure. The average spatial rms’s (uppermost points) represent the typical total empirical noise in each constituent image of the ITF level, and in principle should equal the quadratic sum of the random noise and the “linearization” noise, if the fixed pattern is completely removed.

The empirical total noise lies significantly below the fixed-pattern level inferred from the raw-image analysis, indicating successful removal of that component (although that success is tempered by the addition of “linearization
Fig. 8—Same as Fig. 7, but for the smooth ITF. Here, the individual ITF levels were smoothed slightly before fitting the polynomials to simulate the historical production-processing system, IUESIPS. The smooth linearization mostly fails to remove the pixel-to-pixel sensitivity variations, and the total noise in the corrected images rises to the (high) level of the granularity of the raw images. Now the "linearization noise," assessed from the photometric correction of the unsmoothed ITF level, is large and dominant, while the random noise is still at a low level. The corrected flatfields apparently share a great deal of spatial structure in common: namely, the residual "fixed pattern" of the pixel-to-pixel sensitivity. This is the origin of much of the "noise" in conventionally processed IUE images.

Noise). The solid curve is a fit to the total empirical noise—with a third-order polynomial in powers of \( \sqrt{\text{BFN}} \)—for use later.

Here an important point should be noted. The scaled raw-image noise models for sectors \( \beta \) and \( \gamma \) show significant departures at high intensities from their intrinsic \( \sqrt{\text{signal}} \) behavior when scaled into the BFN domain. The same behavior is seen—although less dramatically—in the empirical (total) noise models derived from the photometrically corrected ITF images. The turn-up at high intensities results from the ITFs themselves, in particular their nonlinear behavior when the SEC target approaches physical saturation (as opposed to telemetry saturation, which simply truncates the curves). The turning up of the noise models indicates that the effective S/N per pixel in linearized images will not improve beyond a critical intensity. In principle that means that deeper exposures, beyond the critical level, will not yield better spectra; although in practice—for emission-line sources at least—that regime rarely would be reached (see Lenz and Ayres 1992; hereafter referred to as LA).

Paper I noted the apparent discordance between the polynomial noise models derived by KBN for IUESIPS-processed low-dispersion spectra, and the ostensible \( \sqrt{\text{DN-NULL}} \) behavior of the raw-image granularity and random noise, without offering an explanation for the discrepancy. Now, it is obvious that incipient physical saturation on the least-sensitive areas of the camera is responsible.

Figures 8(a) and 8(b) depict empirical noise models for the smooth ITF. Here one sees a dramatic change from the phot linearization. The average spatial rms has increased significantly, to the point where it is comparable to the granularity of the raw images. That indicates little success in removing the fixed pattern. Indeed, the "linearization noise" completely dominates the inferred random component (which is comparable to the phot result, as expected), demonstrating that even a relatively mild smoothing of the ITF can have dramatic consequences. The effect is mitigated to some extent in sector \( \gamma \) because the image granularity inherently is smoother there. However, the enhancement in the apparent noise is nearly a factor of 2 at position \( \alpha \), where the images are sharpest. To the extent that the smooth ITF mimics the IUESIPS, one can understand why the IUE Project has devoted significant effort to its NEWSIPS development.

Figures 9(a) and 9(b) depict empirical noise models for the \( \text{rotd} \) ITF. Here, the total, random, and linearization noise components follow the same (desirable) pattern as the phot case, although the overall levels are significantly reduced. The suppression of the noise for the constituent images of the ITF can be traced to the smoothing inherent in the image rotation and post-facto filtering of the photometrically corrected image. Thus, the apparent large reduction in the noise levels with the \( \text{rotd} \) ITF is largely cosmetic, because a proper noise model for that ITF would have to compensate for the known smoothing to recover the "pristine" noise properties (i.e., the pixel-to-pixel noise characteristics in an unmanipulated image).

That, in fact, brings up a related important point. Previously, I noted that sector \( \gamma \) appears to be presmoothed in the raw images, and certainly the raw and phot noise models indicate a large reduction in the apparent granularity...
and random noise at that position in the camera format (for both SWP and LWP). In order to establish the pristine noise characteristics for sector $\gamma$ (and indeed any area of the format) one must determine how much intrinsic smoothing is present. That analysis—via two-dimensional power spectra—will be described in a subsequent section.

While the noise suppression of the rotd ITF compared with the phot ITF for the ITF image collection is expected simply on the basis of the additional manipulations inherent in the former, the real question is whether the rotd approach yields any improvements relative to the straightforward phot strategy for images that are appreciably shifted with respect to the thermally restricted ITF collection. In order to investigate that question, I examined the baseline UV-Flood images (60% exposures for both SWP and LWP) that have been acquired throughout the operational phase of each camera, covering a wide range of camera temperatures. (Here, “camera temperature” is that of the camera head amplifier [THDA] recorded at the time of the READ cycle, as deduced from the round-robin event listing in the image label file). I also included in the analysis the SWP 100% and LWP 80% ITF “tracking” images from the respective ITF campaigns which were not incorporated explicitly in the final coadded ITF levels. The “non-ITF” tracking exposures are valuable for assessing an additional small correction to the noise models that accounts for the fact that the ITF retains some information concerning the specific random noise “pattern” of each of the constituent images. In particular, photometric correction of one of the ITF images should yield a slightly smaller spatial rms than would linearization of a similar UV-Flood image not contained in the ITF collection.

Figures 10(a) and 10(b) depict the deviations of measured rms’s from the empirical noise models for the phot ITF and the collections of tracking exposures, evaluated in sector $\beta$. The deviations are depicted as functions of camera temperature and time during the campaigns. The specific exposures used in constructing the ITF level itself are shown as open circles. It is clear that the images not contained in the ITF show a systematic displacement to higher noise levels relative to the ITF images themselves. The mean deviations range from 5% (sector $\alpha$) to 11% (sectors $\beta$ and $\gamma$) and are similar for both cameras. Furthermore, nearly identical enhancements are obtained for the rotd ITF (with respect to its position-dependent noise models).

Figures 11(a) and 11(b) depict the deviations of the measured rms’s from the empirical noise models for all three prototype ITFs and the collections of baseline UV-Floods. Here, I have attempted to compare the noise properties on the same scale by adjusting the rotd ITF rms’s upward by a factor of 2.26 to compensate for the additional smoothing provided by the image rotation and 1.5 pixel Gaussian spatial filtering. I determined the factor by subjecting random noise fields to the two operations, and conducting many such trials to determine an average noise suppression (the inverse of which is the scaling factor that I applied above).

The horizontal lines in each panel result from a series of simulations in which I shifted each of the five 60% ITF images by 1 pixel in the original line direction prior to applying the photometric correction, and then averaged the resulting empirical/predicted rms values: the solid line is for the phot ITF; the dashed line is for the rotd ITF (as scaled by the noise suppression compensation factor described above).

These diagrams illustrate a number of crucial effects. First, notice the clear systematic increase of the phot ITF noise as one goes to camera temperatures either higher or lower than the nominal temperature of the ITF campaign (i.e., 9.2±0.3 C for SWP). The effect is more pronounced in SWP than LWP. It is due to the subpixel misregistration of the test image and ITF: the thermal shifts of the SWP format are known to be much larger than those of the LWP camera (e.g., Turnrose and Thompson 1984). Notice in both cases that the apparent noise enhancements at the temperature extremes are less than expected for a full 1 pixel displacement. Second, the smooth ITF shows much less variation with camera temperature, but of course is undesirably enhanced (in sector $\beta$) by about 40% at the reference THDA of the ITF campaigns for both cameras. Nevertheless, the smooth ITF does provide some cancellation of the granularity: the double rotation is equivalent in its effect to that of an $\approx 1$ pixel FWHM Gaussian, which suppresses the pixel-to-pixel structure but does not remove it entirely. Third, the rotd ITF not only shows a flatter dependence on THDA than the phot ITF, but also has the desirable low noise characteristics at the reference ITF temperature. Indeed the 1 pixel test for the rotd ITF shows a substantial improvement compared with that for the phot.
with respect to the phot noise model. The ratios for the rot ITF were scaled upward by a constant factor to compensate for the overt smoothing of the initial rotation and post-facto Gaussian filtering. The comparisons with respect to camera temperature are revealing because small thermally induced image shifts are believed to be the major source of "misregistration noise" (see, e.g., Paper I). The horizontal dark line indicates the average result of photometrically correcting images that were intentionally shifted by 1 pixel in the "LINE" direction for the phot ITF, and the dashed horizontal line indicates the result for the rot ITF including the compensation factor.

That behavior indicates that the preconditioning of the images in the rot ITF processing (through the initial rotation) helps to mitigate the influence of the subpixel thermal shifts. Nevertheless, at the temperature extremes in SWP, the apparent noise enhancement still is about 40% over the ideal level (1.1×phot ITF noise model) expected for a non-ITF UV-Flood image. Potentially, the cross-correlation registration strategy embodied in NEWSIPS could significantly close that gap, although it remains to be seen in practice whether such improvements can be obtained. [In any event, the vast majority of SWP science images have been taken within ±2°C of the nominal ITF THDA, where the performance of the rot ITF is close to the ideal, and it does enjoy a considerable advantage in CPU speed over the NEWSIPS approach. For these reasons—and because the NEWSIPS software was still proprietary at the time—I adopted the rot ITF in an SWP-LO processing package for chromospheric emission-line stars (see ABLB).]

An important practical point is that the phot ITF provides close to the ideal linearization of even the most recent images, at least those obtained near the nominal ITF THDA. That indicates that the granularity of the cameras has not changed appreciably in the intervening ~6 years, thus a single ITF should be applicable in principle to the entire collection of images. It should be noted in this regard that the apparent deviations of the LWP points in recent years is due mostly to the fact that the nominal LWP THDA currently is more than a degree higher than during the 1984 ITF campaign, presumably related to a change in the thermal environment of the instrument bay when NW became the operational camera in place of NR (which had experienced an undesirable persistent image anomaly—the "flare"—in that timeframe). In 1992 May, the IUE project conducted another LWP ITF campaign in which the camera THDA was stabilized at a value more appropriate to the average level experienced since the previous calibration.

A final point is illustrated in Fig. 12, which is analogous to Fig. 10(a), but for position α. The shaded symbols in the frame correspond to a series of T-Flood flatfield exposures that were recorded during the SWP ITF campaign, and linearized using the phot ITF. The T-Flood exposures were obtained with a different set of lamps—tungsten filament—than the UV-Flood ITF calibration images. The tungsten lamps emit virtually no UV light, but the photocathodes of the IUE cameras respond to them through a very weak sensitivity tail into the visible. The T-Flood images are overexposed at positions β and γ, and show a gradient of intensity—following linearization—across position α (unlike the UV-Flood images which truly are flat by operational definition). Thus I subtracted a heavily smoothed version of each photometrically corrected T-Flood image prior to assessing the spatial rms, to avoid the bias that otherwise would be introduced by the intensity gradient. It is clear that the T-Floods linearize as well as the UV-Flood images, as long as they are close to the ITF THDA. That indicates that the T-Floods linearize as well as the UV-Flood images, due to the INFFITs of both SWP and LWP are created with the same monochromatic light (2500 Å mercury pen ray). While the similarity between
the optical and mid-UV granularity does not prove that the far-UV granularity also is the same, it does provide some hope that the dominant source of the pixel-to-pixel sensitivity variations are in the camera target, rather than in the first-stage photocathode. If that is the case, the granularity will be the same at all wavelengths because the input to the SEC stage (blue photons from the image converter: see below) is itself monochromatic. Achromatic granularity by a defocused read beam (Coleman and Snijders 1977).

The discussion of the properties of the alternative photometric corrections outside of the ITF collection is somewhat of a digression from the main focus of the paper, namely, the noise properties of SWP and LWP. To complete that topic, I next turn to an examination of the noise filtering properties at the different spatial positions in the camera formats.

### 3.3 Spatial Filtering

The image that falls on the camera faceplate suffers a variety of transformations before it is ultimately radiated down to the ground station in digital form. The UV light from the spectrograph (or internal calibration lamps) first is translated into photoelectrons in an image conversion and intensification stage. The photoelectrons are accelerated into a phosphor to liberate blue photons, and the resulting monochromatic optical image is recorded by an integrating television camera. In the latter, again the impinging light is converted to photoelectrons which in turn are accelerated through a large potential difference and electrostatically focused onto the camera target. There the fast electrons collide with bound electrons of the insulating substrate, freeing some of them and creating pockets of positive charge. The depth of the positive charge is proportional to the integrated photoelectron deposition, although with sufficient charge accumulation a physical saturation of the target occurs (due to lack of negative charges to free; other related effects—like halation—also occur at high intensities). Following the integration period, the camera target is discharged with a scanning electron beam, and the residual current is converted to a digital signal which then is radioed to the ground. One can imagine that there are many opportunities during these several distinct steps to add noise to the detected signal, or to modify the noise contributed by previous stages of the process.

What one ultimately wants to know is the character of the random noise (supposing that the systematic components can be removed successfully through the photometric linearization procedure) on a grid of statistically independent pixels. The latter requirement is crucial in a variety of applications [like Optimal extraction (KBN) and Gaussian fitting (e.g., LA)] where the proper propagation of errors or evaluation of flux uncertainties relies on the implicit assumption of statistical independence between the pixel intensities. The practical implication here is: I have evaluated the noise properties of the flatfield images through, in essence, the spatial rms of the photometrically corrected intensities. If the images have experienced any filtering of their noise properties, the apparent rms will be depressed compared with the true intrinsic noise (on that particular pixel grid). Thus the empirically derived noise model will underestimate the true noise values for the given pixel grid. One way to compensate for any spatial filtering is to resample the grid post-facto. Another way is to retain the given pixel grid but augment the empirical noise model by the inverse of the noise suppression factor appropriate for whatever level of filtering is present. The trick is to establish that level of smoothing from the images themselves. The obvious approach is to use 2-D Fourier analysis.

Accordingly I collected a subset of 15 of the 100% SWP (and 80% LWP) tracking exposures from the ITF campaign which were not one of the five images included in that particular ITF level and which fell within a narrow range of THDA. I photometrically corrected the images using the phot ITF, and subtracted a spatially filtered version of the image to remove any large-scale trends. I apodized the $64 \times 64$ frames (for the sectors $\alpha$, $\beta$, and $\gamma$) to zero beyond a 50 pixel diameter central zone using a cosine “ring,” and divided the net intensities by the rms to normalize the power spectrum. I then averaged the 2-D Fourier amplitudes over the 15 images of each set to improve the statistics. Figures 13(a) and 13(b), illustrate the results for SWP and LWP, respectively. The profiles in each panel were obtained by annular averages of the 2-D power spectra up to a critical frequency (to emphasize the symmetric components of the low-frequency power), after which point the tracings are column averages [to emphasize the power spikes due to microphonics (see below)]. At the same time, I conducted a series of numerical experiments with random noise fields prefìltered in a variety of ways, but Fourier analyzed in exactly the same manner as the IUE images.

Qualitatively, both cameras show the same behavior as a function of position: sector $\alpha$ displays a relatively flat power spectrum indicating little or no spatial filtering; sector $\beta$ displays a power spectrum slightly tilted toward the low frequencies indicating a mild smoothing; while sector $\gamma$ displays a power spectrum distinctly rising at low frequencies, indicating more substantial smoothing. However, even though sector $\gamma$ shows evidence of smoothing at low frequencies, note that the power spectrum levels out at higher frequencies unlike the behavior of a simple random noise field that has been spatially filtered with a Gaussian.

Figure 14(a) illustrates the power spectra expected in the latter situation. The appearance of the sector $\gamma$ power spectrum suggests a combination of filtered and unfiltered random noise fields. Examples are provided in Fig. 14(b). One can imagine, for example, that the intrinsic random noise fluctuations on the SEC target are more or less smoothed as a function of spatial position on the camera depending on details of the reading process, particularly...
Fig. 13—Two-dimensional power spectra averaged over 15 ITF “tracking” images for each camera, linearized with the phot ITF. A filtered mean was subtracted from each sector, and the resulting image was divided by its rms and apodized outside of a 50 pixel diameter circle, prior to calculating the Fourier transform. The line plots depict annular averages of the power spectra up to a frequency of 0.3 pix$^{-1}$, to emphasize any radially symmetric components of the power; and a column average at higher frequencies to emphasize the microphonic noise “spots.” The ordinate is the amplitude of the power spectrum normalized to that expected for a white-noise field similarly processed. The slight curvature of each spectrum at the lowest frequencies is a consequence of the apodization. The zero frequency value is suppressed (it is zero; each fluctuation image has an integral of zero). In both cameras, sector $\alpha$ shows a relatively flat power spectrum, like that of white noise; while sector $\gamma$ shows a distinct rise in power toward low frequencies suggesting some prefiltering.

the focus of the read beam (which varies owing to nonuniformities in the controlling fields). However, the signal from the camera target could then suffer an additional infusion of (unsmoothed) random noise, for example in the A/D converters. Table 2 summarizes my evaluation of the apparent smoothing in each of the three sectors, and the compensation factors for the degree of noise suppression (as deduced from the numerical simulations).

3.4 Microphonics

An additional, subtle, source of “noise” in IUE images is the presence of microphonics: (usually) low-amplitude “waves” of spatially varying period which are most obvious on the raw images outside of the target ring. The microphonics arise from ambient mechanical vibrations of the camera during the read process. The phase of the disturbance is interrupted by regular pauses of the read to insert

<table>
<thead>
<tr>
<th>Position</th>
<th>non-ITF</th>
<th>spatial filtering</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>1.05</td>
<td>$\approx 1$ [little or none]</td>
<td>1.1</td>
</tr>
<tr>
<td>$\beta$</td>
<td>1.10</td>
<td>1.3 [FWHM$\approx 1; f \approx 0$]</td>
<td>1.4</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>1.11</td>
<td>2.0 [FWHM$\approx 2; f \approx 0.3$]</td>
<td>2.2</td>
</tr>
</tbody>
</table>

LWP

| $\alpha$ | 1.06 | $\approx 1$ [little or none] | 1.1   |
| $\beta$  | 1.07 | 1.3 [FWHM$\approx 1; f \approx 0$] | 1.4   |
| $\gamma$ | 1.06 | 2.0 [FWHM$\approx 2; f \approx 0.3$] | 2.2   |

The empirical power spectra of sector $\gamma$ resemble the panel (b) situation with $f \approx 0.3$. The implied presmoothing must be taken into account when deriving “pristine” noise models.

Fig. 14—Comparison of power spectra of random noise fields subjected to varying degrees of filtering and analyzed in the same way as the IUE flatfields. Each power spectrum is an average of 20 independent trials. In panel (a), the noise fields were filtered with two-dimensional Gaussians of the indicated FWHM: “0” indicates the undisturbed white-noise case (and source of the “W-N” normalization). The smoothing redistributes power from the high frequencies to the larger spatial scales. Panel (b) depicts the case of a random noise field that is filtered with a FWHM$=2$ pixel Gaussian and then combined with a unadulterated noise field (having a share “f” of the total). The case $f=0$ corresponds to the pure smoothing of panel (a), while the case $f\approx 1$ corresponds to domination by the unfiltered component. The empirical power spectra of sector $\gamma$ resemble the panel (b) situation with $f\approx 0.3$. The implied presmoothing must be taken into account when deriving “pristine” noise models.
amplitude cannot be predicted a priori and might be difficult
noise models to arbitrary science images, because the am-
introduces some uncertainty in the practical application of
both cameras.

On the one hand, the presence of the microphonics in-
troduces some uncertainty in the practical application of noise models to arbitrary science images, because the amplitude cannot be predicted a priori and might be difficult to measure directly with power-spectrum techniques in the general case (for example a highly structured image of a low-dispersion stellar spectrum). On the other hand, the amplitude usually is small, and is incorporated in the empirical noise models to whatever extent the ITF UV-Floods experienced a normal range of microphonics.

I have noticed a number of science images, particularly from early in the IUE mission (before measures were taken to minimize spacecraft vibrations during reads), where the microphonic waves are quite noticeable and significantly affect the extracted stellar spectrum. In such cases the average noise models will apply only as lower bounds to the true spatial rms in the linearized image and in the extracted spectrum. Fortunately the extreme cases are relatively rare (and are easily recognized).

3.5 Particle Radiation Noise

Up to this point I have intentionally ignored one of the most significant sources of "noise" in IUE spectral images, namely, that due to cosmic particle radiation. The ITF images are virtually free of such contamination, because the calibration campaigns were conducted during low-radiation conditions and the UV-Flood exposures themselves typically are quite short. Nevertheless, the corrupting effect of the particle radiation can overwhelm the other noise sources in certain types of scientific observations.

The particle radiation manifests itself in two ways. First, there is a diffuse source of "fogging" due to the emission of (optical) Cerenkov radiation as fast particles interact with the magnesium-fluoride window of the camera. Second, there are bright spots ("hits") caused by direct excitation of the phosphor in the image converter or possibly the camera target itself.

On the one hand, the particle fogging affects the noise level in a scientific exposure indirectly by raising the diffuse background level upon which the spectrum sits. The S/N is reduced by a high background because the signal is determined by the total DN minus the background, whereas the noise is determined by the total DN alone. Fortunately, the indirect influence of a high background (regardless of whether it arises from particle fogging or from detector "dark current") can be tracked accurately in the extraction step by properly assigning noise levels based on the gross signal prior to subtracting a filtered background to determine the net intensities.

On the other hand, the influence of the bright-spot component of the particle radiation varies enormously, and is difficult to quantify in general. A single well-placed hit can ruin a deep exposure of a faint emission-line object; whereas an image inundated by bright spots might still be usable if key spectral features had avoided contamination. Optimal extraction procedures, like that described by KBN, can suppress near-spectrum bright spots. Such techniques are of little use, however, if the bright spots dominate the footprint of a faint emission-line spectrum, preventing the determination of a reliable cross-dispersion profile. In my own experience in cataloging several thousand SWP-LO spectra of chromospheric emission-line stars, I rarely have found an exposure longer than 4 hr (of a faint source) that was not corrupted to some degree by bright spots. Most of such exposures were taken during "low-radiation" US1 and Vilspa time, so there is no safe haven from the cosmic rays. Paper I proposed that the rising backgrounds due to detector dark current (and residual phosphorescence in the image converter) set a natural limit of about 1 shift (8 hr) on the exposure time to obtain maximum S/N on a faint target. My more recent experience with bright spots suggests that the true limit is closer to 1/2 shift (4 hr), particularly if the target spectrum is dominantly narrow emission lines. (In the opposite case of a broad featureless continuum—say, a BL Lac object—one can tolerate higher bright-spot contamination, because the underlying signal can be recovered more successfully using spatial filtering techniques along the dispersion.)

3.6 Pristine Noise Models

Putting aside the unpredictable noise contributed by microphonics and cosmic radiation, one can construct "pristine" noise models for the two cameras based on the photometric considerations discussed in Secs. 3.2 and 3.3. The unadulterated noise models simply are the fundamental relations derived from the photometrically corrected ITF constituent images (phot ITF), multiplied by a small correction factor ($\approx 1.1$) derived from the photometrically corrected "non-ITF" tracking images from the ITF campaigns, and then by a second correction factor derived from the spatial power-spectrum analysis to account for any prefiltering of the noise properties.

Figures 15(a) and 15(b) compare the resulting pristine noise models for the three positions on the two cameras. Remarkably, despite the rather large spatial dependence of the fundamental ITF noise models, the corrected models are nearly identical to one another (over the unsaturated regime of BFN at each position), with the blatant exception of sector $a$ of the LWP camera.

4. CONCLUSIONS

Regardless of its ultimate source(s), the intrinsic noise in the IUE cameras appears to be relatively independent of position. Consequently, one can simplify the prescriptions given in Paper I by adopting a unified value of the coefficient in the relation $\sigma_{DN} \approx a \sqrt{DN-\text{NULL}}$. A reasonable choice would be $a \approx 1$ for the purpose of predicting exposure times using the estimators provided in Paper I. The
Fig. 15—Pristine noise models for both cameras. These are obtained by adjusting the empirical models according to the two compensation factors described in the text. The shaded areas, barely visible in the case of SWP, indicate the maximum and minimum extents of the three noise models. Aside from the anomalous sector \( \alpha \) of LWP, the intrinsic noise functions appear to be nearly independent of position within each camera (at least along the footprint of the low-dispersion spectrum), and in fact are rather similar between the cameras.

Estimators would be reliable up to a critical peak DN (the top of the linear regime of the ITF), which varies with position: about 175 DN in sector \( \alpha \), 210 in \( \beta \), and 245 in \( \gamma \). The fact that the intrinsic noise appears to be independent of position and depends in a simple way on intensity suggests the dominant underlying source might simply be shot noise in the photoelectron production in the first-stage image converter. Other sources like A/D conversion and microphonics appear to be less important, and are manifested primarily at low intensities and on those parts of the camera that suffer filtering of the shot-noise component.

The maximum intrinsic S/N per pixel is about 12, although it would appear to be larger in sector \( \gamma \) owing to the prefiltering. The effective S/N per wavelength point in a low-dispersion spectrum would be significantly higher than the intrinsic S/N per pixel, roughly as the square-root of the number of cross-dispersion pixels in the extraction “window.” The ultimate S/N of a line flux measurement would be higher still, because several wavelength points would constitute the emission-line profile (cf., LA). Thus, the intrinsic maximum S/N per pixel of the vidicon detectors might appear to be rather modest, but one nevertheless can achieve a respectable few percent precision in the measurement of emission-line fluxes in properly linearized well-exposed \textit{IUE} spectra of late-type stars (e.g., ABLB).

That is considerably better than the anecdotal limit of 10% widely quoted by experienced \textit{IUE} observers, a perception undoubtedly flavored to a large extent by the noisy photometric correction provided by the \textit{IUESIPS}. However, the more realistic—smaller—noise levels in properly processed \textit{IUE} spectra, such as by \textit{NEWSIPS} or alternative approaches, might encourage investigators to consider the use of the \textit{IUE} in specialized high-precision observing programs of the future, and certainly broadens the horizons of archival studies in the vast existing collection of \textit{IUE} spectra.

My study has benefitted greatly from many conversations with the staff of the \textit{IUE} Project, and with members of the Final Archive Definition Committee. I thank in particular C. Imhoff, A. Kinney, and E. W. Brugel. The several hundred \textit{IUE} raw images used in the analysis were obtained from the National Space Sciences Data Center using the NDADS electronic mail retrieval system. This work was supported by NASA grant No. NAG5-1215.

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