Infrared Imaging Systems: Design, Analysis, Modeling, and Testing

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Infrared Imaging Systems: Design, Analysis, Modeling, and Testing

Gerald C. Holst
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INFRARED IMAGING SYSTEMS:
DESIGN, ANALYSIS, MODELING, AND TESTING

Volume 1309

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Conference 1309, *Infrared Imaging Systems: Design, Analysis, Modeling, and Testing,* was part of a two-conference program on Electro-Optic Analysis and Testing held at the SPIE Technical Symposium on Optical Engineering and Photonics in Aerospace Sensing, 16–20 April 1990, in Orlando, Florida. The other conference was:

Conference 1310, *Signal and Image Processing Systems and Performance Evaluation.*

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INTRODUCTION

The analysis, modeling, and testing of infrared systems has not kept pace with the evolution of sampled data systems employing digital scan converters, SPRITE detectors, and focal plane arrays. These emerging technologies have created new design considerations for human observers, trackers, and automatic target recognizers. This conference focused on systems issues. The research, design, fabrication, and testing of components were presented at companion conferences.

Since design, analysis, and modeling are interrelated, papers in these areas were presented in five sessions and state-of-the-art testing was presented in two sessions. One of the testing sessions was devoted entirely to Canadian infrared testing techniques.

Harold Kennedy set the tone of the conference with his invited paper "Modeling second-generation thermal imaging sensors." The keen interest in focal plane array modeling and sampled data effects was evident by the number of papers presented in this area and the large attendance. The question-and-answer period after each paper was lively and interesting, and small, focused discussions on thermal imaging systems took place during breaks and after the conference.

It was indeed a pleasure to see so many outstanding papers presented in this conference. The quality of the papers and the large audience has led to scheduling this conference at SPIE's 1991 Orlando meeting.

I would like to thank all the authors for their contributions and hard work. The conference was successful due to the efforts of the cochairs John A. D'Agostino, Carl E. Halford, James Ratches, Stephen W. McHugh, and Paul J. Jennison. I acknowledge their efforts and express my sincere appreciation to all of them.

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INFRARED IMAGING SYSTEMS:
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SESSION 1

Infrared System Design, Analysis, and Modeling I

Chair

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Modeling Second Generation Thermal Imaging Systems

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ABSTRACT

Analytical models of thermal imaging system performance have gradually become obsolete as TIS (thermal imaging systems) have become more complex and have improved in vertical performance. In particular, the effects of sampling and aliasing have not been included directly, but have had to be accounted for by side calculations before entering the data. In this paper, an approach to modeling second generation TIS is described in which the effects of sampling on both signal and noise are accounted for without requiring the user to make subsidiary calculations. The model is two-dimensional, using both vertical and horizontal resolution in the prediction of recognition and detection performance. A model for human perception is presented which differs slightly from the matched filter concept models and gives a closer match to measured data. The differences between modeling scanning and staring systems is discussed, as well as between systems with on-focal- rather than off-focal-plane sampling. Proper treatment of the several sources of noise in sampled systems is analyzed, including aliased noise.

1 BACKGROUND

As second generation Thermal Imaging Systems (TIS) have developed, it has become evident that new performance models are needed for these systems. The standard model in the industry, the so-called NVL Model[1], is inconvenient at best and inadequate at worst, for the prediction of performance of these advanced systems. I proposed an improved, two-dimensional performance model[2] in 1983. This paper will describe enhancements to the latter, emphasizing the differences between first and second generation TIS and giving analytical form to modeling these differences.

2 DIFFERENCES BETWEEN FIRST AND SECOND GENERATION TIS

2.1 Sampling

Few first generation TIS employ sampling. Staring arrays are quite primitive, with poor sensitivity and few elements. Scanning arrays sample the vertical field of view by raster scanning, but, with a few exceptions, do not employ sampling in the scan direction. Most are "Electro-optically multiplexed" systems which create a scene in the visible or near infrared by using an array of modulated light emitting diodes with a one-to-one correspondence with the elements of the detector array.

By contrast, most second generation TIS will employ sampling in two dimensions. Staring arrays with good sensitivity and many elements are coming into production. Improved devices will allow high data rate sampling of scanning systems to be processed. Components capable of high speed analog to digital conversion will allow digital signal processing of TIS signals.

2.2 Detector

Most first generation detectors make use of photoconductive or photodiode elements. With the exception of the SPRITE detector, these detectors affect the system MTF only through the detector dimensions and the detector time constant or frequency response. Detector elements are continually biased and produce continuous signal outputs. If the signals are sampled or multiplexed, the process takes place external to the detector/dewar.

Second generation detector arrays are expected to make use of sampling at the detector element itself. The signal will be allowed to charge up a storage element for a period of time before being sampled, reset, and the process repeated. This "at-the-element" or "on-focal-plane" sampling adds an additional MTF contribution to scanning TIS. It also changes the nature of the detector output signals from a set of continuous, parallel, analog outputs, one from each element, to an arbitrary number of multiplexed outputs, each of which is a serial combination of samples from several detector elements.

2.3 DC Restoration

Signal processing of first generation TIS generally consists of a series of AC coupled amplifiers. DC restoration is rarely employed. Second generation TIS, however, will almost surely employ some form of DC restoration. Whatever means is used to accomplish the DC restoration, it will cause both the type, magnitude, and frequency content of the noise to be different from that of first generation TIS.

2.4 Displays

The display devices used with first generation TIS include CRTs, Image Intensifier tubes, and Light Emitting Diode arrays. These are viewed directly or through various monocular and biocular optical systems. All have the common attributes that the displayed image brightness varies continuously and smoothly in one direction and have a raster structure in the other. Most second generation TIS will be the same, mostly using CRTs - sometimes with auxiliary optical systems. Some second generation systems may find it advantageous to use one of the discrete element displays now becoming available. The post-filtering characteristics of these devices will be markedly different from those of the one-dimensional raster devices of first generation devices.

2.5 Electronic Signal Processing Output

Signal processing of first generation TIS signals is essentially limited to that required to make a good visual presentation to an operator. The only further electronic processing that is at all common is one of several video tracking algorithms. One of the major thrusts of second generation TIS development will be to provide an output which is compatible with the requirements of automatic target detection (ATD), screening (ATS), and recognition (ATR) by the application of appropriate algorithms. Both the algorithms and their requirements are still ill-defined, but there is little doubt that some form of ATD, ATS, or ATR output will be a requirement for future TIS.

3 APPROACHES TO MODELING SECOND GENERATION TIS

3.1 Sampling

The standard first generation model ignores all sampling effects. For scanning systems, the assumption is implicit in the model that if the data is sampled, it is done at a rate high enough to avoid any aliasing effects. It is left up to the user to determine any detrimental effects that occur if this assumption is not valid. For lattice sampling in staring systems and for the sampling effected by the raster for scanning systems, any aliasing effects are included indirectly by the manner in which the models were calibrated against measured data.

Second generation modeling must take account of the several effects of sampling. Programs must include models for aliasing of noise and signals, the fixed pattern noise, quantization of samples, and the additional filters that are necessary for proper sampling and reconstruction of imagery.

3.1.1 Modeling Sampling Effects

The effects of sampling can be negligible or they can dominate the performance of a TIS. In those cases in which adequate sampling, filtering, and amplitude resolution can be accomplished, the performance of a TIS employing sampling can be identical to one in which the signal is continuous. Constraints of weight, power, component availability, processing speed, etc., often force design choices to be made which limit the performance of a sampled-data TIS. The performance loss may take the form of reduced spatial resolution or discrimination, decreased signal to noise ratio, or an increase in the amount of distracting spurious information.

> Note: For a TIS employing sampling of the infrared scene (or the signal derived from scanning the scene), the abbreviations **S-TIS** will be used. For a TIS in which the signal retained in continuous form - that is, not sampled, - the abbreviation **NS-TIS** will be used.

3.1.1.1 Modeling Aliasing

3.1.1.1.1 Modeling Signal Aliasing

Information theory gives the result that if the signal being sampled contains information with frequency content greater than half the sampling frequency, the resulting samples carry spurious information. That is, the image reconstructed from these samples will be distorted by the spurious or aliased information. In order to reproduce or reconstruct a perfect image of the original signal, the sampling frequency must be greater than twice the highest frequency contained in the signal. Practically speaking, the input signal must have no frequency content greater the Nyquist frequency f_N, or the signal must be "pre-filtered" to remove all higher frequency content. Furthermore, when the image is reconstructed by placing the samples in the same sequence in which they were originally sampled, they must be "post filtered" to remove all frequency content above f_N which may have been introduced in the reconstruction process.

In the event that it is not practical or possible to prefilter the signal prior to sampling or to adequately post-filter the reconstructed signal, the result will be an imperfect image of the original signal and may contain spurious detail not present in the original image. Mathematically, the value of the frequency spectrum of the reconstructed image $I_r(f)$ at the frequency f can be written

$$I_r(f) = MTF_{rf}(f) \sum_{n=0}^{\infty} I(nf_s \pm f) \qquad (1.)$$

$$I_r(f) = MTF_{rf}(f) I(f) + MTF_{rf}(f) \sum_{n=1}^{\infty} I(nf_s \pm f) \qquad (2.)$$

where $MTF_{rf}(f)$ is the transfer function of the reconstruction or post filter, $I(f)$ is the frequency spectrum (Fourier transform) of the input signal (after pre-filtering), and nf_s is a multiple of the sampling frequency f_s.

The first term in the expression for the reconstructed signal is simply the spectrum of the original (pre-filtered) signal, filtered by the reconstruction filter. The remaining terms, however, represent the aliased information - that is, the information not present in the original signal.

There have been many attempts to define quantitative measures for aliasing. Because aliasing is scene dependent, however, it becomes a formidable task to calculate the amount of aliasing in a complex scene. I propose that a reasonable measure of the propensity of a TIS to generate aliasing is the "spurious response" function defined by Schade[3]. In the present notation, this is just the lowest frequency term of the aliased information summation above:

$$Ail(f) = MTF_{rf}(f)I(f_s - f) \qquad (3.)$$

This expression represents most of the spurious information resulting from sampling a point source - one with equal information content at all frequencies. It comes close to being a measure of the worst case aliasing for a scene with no strong periodic content. As an example, consider a slightly under-sampled (or underfiltered, if you prefer) TIS with the prefiltered MTF shown in Figure 1. Note that significant response exists beyond the Nyquist frequency f_N.

Figure 2 shows the "folded back" spectrum both before and after filtering by a typical post filter response, also shown in the figure. Finally, Figure 3 shows a comparison of the spurious response to the direct, un-aliased overall system response. Shade's measure of aliasing is the ratio of the area under the curve of spurious response, divided by the area under the direct response. For this example, the spurious response is about 12 percent of the direct response.

3.1.1.1.2 Modeling Noise Aliasing

Another result of employing sampling in processing the signal data in a TIS is that the way in which noise is analyzed must be modified. In a NS-TIS, the noise power spectrum is a meaningful measure of the noise at any point in the signal processing chain. Similarly, the integral of the noise power spectrum over frequency is a measure of the noise variance, and the noise bandwidth is defined as the noise variance divided by a reference value of the noise power spectral density.

$$f_n = \frac{\int_0^\infty S_n(f)[MTF_n(f)]^2 df}{S_{no}} \qquad (4.)$$

where $S_n(f)$ is the noise power spectral density referred to the detector output, S_{no} is a reference value for the spectral density, and $MTF_n(f)$ is the composite MTF of all components from the detector to the point of measurement.

The situation is different for S-TIS. Here, the noise power spectrum loses its meaning after the data has been sampled, and only recovers meaning after the signal has been reconstructed. When the data is sampled, each sample is "frozen" at the value it had when the sample was taken, and noise has meaning only as the variance of the collection of samples. Neither an "image" nor a "noise power spectrum" exist as such when in the sampled data format. When reconstructed - that is, put back into the same spatial or temporal sequence as the original scene, the noise power spectrum again has meaning, but its value will have changed, in general, because of the sampling process. An expression for the modified noise spectrum is

$$S_{nr}(f) = [MTF_{rf}(f)]^2 S_n(f) + [MTF_{rf}(f)]^2 \sum_{n=1}^{\infty} S_n(f + nf_s) \qquad (5.)$$

Note the similarity of this expression to that of equation 2 for the signal spectrum. It is different because $S_n(f)$ is a power spectrum rather than an amplitude spectrum like $I(f)$. The noise expression shows that spurious noise is added to the reconstructed image unless adequate pre- and post-filtering is accomplished. This noise is, in effect, folded back from the sampling frequency and its multiples, as shown in the expression. Equation 5 shows that it is not sufficient only to prefilter the noise, but that a post filter (or reconstruction filter) with a sharp cutoff near Nyquist must also be used.

The above expression is applicable to all S-TIS. It requires some interpretation for TIS in which the sampling takes place on the focal plane, at a detector element unit cell. For the on-focal-plane-sampled case, the noise power spectrum is a meaningless quantity, since a continuous signal never exists. The only meaningful quantity is the variance of the sequence of samples taken of the signal at a given unit cell. The sample-to-sample variation at this point is proportional to the square root of the total number of signal carriers collected per sample and thus to the square root of the time over which each sample is collected. Since the amplitude of the detected signal is proportional to the integration time, it follows that the sample variance is inversely proportional to the square root of the integration time.

Although noise bandwidth is an essentially meaningless quantity at this point, since it is not a directly measurable quantity, it is nevertheless useful to note that the sample variance for the on-focal-plane-sampled case is the same as would be obtained for a noise bandwidth

$$f_n = \frac{1}{2\tau_i} \qquad (6.)$$

where τ_i is the integration time.

This equivalency is the meaning of the statement sometimes heard that the noise bandwidth of second generation TIS is set by the on-focal-plane integration time. The expression assumes that noise power spectral densities are represented by single-sided frequency, and that there is no accumulation or summation of multiple samples. When an image is reconstructed from the samples in this case, the noise power spectrum prior to postfiltering may be taken to be white.

3.1.1.2 Modeling Quantization Noise

Quantizing the data by means of an analog to digital (A/D) convertor can have an effect on TIS performance. If adequate amplitude resolution in the quantization process is not used, the difference between the exact value and the nearest quantized value of a sample represents an additional uncertainty in the data. This uncertainty results in an apparent increase in the rms noise of the reconstructed image.

An approximate expression for the ratio of the rms noise at the A/D output to that at the input is

$$\frac{\sigma_{out}}{\sigma_{in}} = \left[1 + \frac{\left(\frac{q}{\sigma_{in}}\right)^2}{12}\right]^{1/2} \qquad (7.)$$

where σ_{in} is the input rms noise level, σ_{out} is the output rms noise level, and q is the least significant bit (LSB) of the A/D quantization.

This expression is quite accurate for LSB-to-rms noise ratios of 2 or less. In a well-designed system, a ratio of greater than 2 will only occur for situations in which the signal level is so high that an increase in the noise level is of no concern. The region of most interest is that for which the LSB is equal to or less than the input rms level. For this part of the curve, the output rms noise level is adequately represented by the expression above.

3.1.1.3 Modeling On-Focal-Plane Sampling MTF

Another significant effect of on-focal-plane sampling is the additional MTF factor that results from integrating the detected radiant signal over a finite time interval. The additional MTF has the form

$$MTF_i = \frac{\sin(\pi f \tau_i)}{\pi f \tau_i} \qquad (8.)$$

This expression assumes that there is only one integration time interval per sample interval. If two or more integrations are summed, the MTF expression becomes more complicated. The more complex function deviates appreciably from the simple expression only at frequencies well above Nyquist, however, so that the simpler expression is adequate for all cases of practical interest.

3.1.2 Modeling Fixed Pattern Noise

There are several sources and types of fixed pattern noise which can appear in the output of a TIS. All types of fixed pattern noise can be characterized by their correlation pattern; that is, the degree to which various patterns of pixels evidence similar variations. This section discusses those categories of fixed pattern noise which are most commonly observed in TIS. The causes of the various correlations are not the issue here, but include optical or electrical crosstalk, noisy references for normalization, different response efficiency to thermal references than to scene radiation, non-linear detector channel transfer functions, etc. Each of the types of fixed pattern noise (FPN) has a different effect on NET and MRT. A formula for modeling the effects of each type is given in this section.

3.1.2.1 Modeling Noise that is Fixed and Uncorrelated from Sample to Sample

For this case, a measurement of the rms noise of after reconstruction of the sampled data would not distinguish between time varying and fixed noise. The total variance of the sequence of samples in a single frame from different detector channels would be simply the uncorrelated sum of variances of the random, time-varying noise (TVN) and fixed-pattern noises. To model the effect this type of FPN has on NET, calculate the resultant NET by scaling the usual NET in this manner:

$$NET' = k_{var} NET_o \qquad (9.)$$

where

$$k_{var} = \left[1 + \left(\frac{\sigma_{fp}}{\sigma_o}\right)^2\right]^{1/2} \qquad (10.)$$

NET_o is the NET calculated using only the TVN, σ_o^2 is the variance of the TVN, and σ_{fp}^2 the variance of the FPN.

A similar modeling applies to MRT, either scan or cross scan, except that temporal averaging of the FPN is different from that of the TVN. The correction factor for temporal averaging is

$$k_{temp} = \left[1 + \left(\frac{f_F t_{eye} \sigma_{fp}}{\sigma_o}\right)^2\right]^{1/2} \qquad (11.)$$

where f_F is the frame rate, and t_{eye} is the eye integration time.

$$MRT' = k_{temp} k_{var} MRT_o \qquad (12.)$$

where MRT_o is the MRT calculated using only the time varying, random noise. Note that the NET value used in calculating MRT_o is NET_o, the NET for random TVN only, and that the usual temporal averaging factor $\sqrt{f_F t_{eye}}$ is used in addition to the correction factor k_{temp}.

3.1.2.2 Modeling Noise that is Time Varying and Uncorrelated Line-to-line, but Correlated along a Line

The effect of this FPN differs depending on the direction of measurement assumed. If NET is computed from the variance of samples along a line, the cross-line variances will have no effect and the NET will equal NET_o. If computed from variances of samples in the cross line direction, the variance σ_{lfp}^2 of this noise adds to the random TVN:

$$NET' = k_{var} NET_o = \left[1 + \left(\frac{\sigma_{lfp}}{\sigma_o}\right)^2\right]^{1/2} NET_o \qquad (13.)$$

Spatial integration of the correlated samples causes the resultant MRT to be given by:

$$MRT' = k_{lvar} MRT_o = \left[1 + k_W \left(\frac{\sigma_{lfp}}{\sigma_o}\right)^2\right]^{1/2} MRT_o \qquad (14.)$$

where

k_W = the number of correlated noise areas along the line and within one MRT bar. (15.)

3.1.2.3 Modeling Noise that is Fixed and Uncorrelated Line-to-line, but Correlated along a Line

Fixed, line-correlated noise effects NET in the same manner as time varying. It effects cross-line MRT differently because the difference in temporal averaging of the TVN and FPN must be included:

$$MRT' = k_{temp} k_{lvar} MRT_o \qquad (16.)$$

3.1.3 Modeling DC Restoration Effects

There are two major effects that can result from DC Restoration of TIS video. The first is a "setting in" of a fixed line to line variation. If a noisy or reference is used in DC restoration or if the restored level has a quantization error, the result will be line-to-line variation in displayed brightness. This variation can have a degrading effect on TIS performance, and was described in the preceding section.

A second effect of DC restoration can improve the apparent quality of displayed TIS imagery and improve performance for some scenes. The effect is the reduction of low frequency noise that results from the high-pass filtering nature of DC restoration. Qualitatively, low frequency noise is reduced because no excursion can persist for a longer period than the clamping period. Thus any noise power below the clamp frequency - usually the frame frequency - is reduced. Modeling the filter effect is difficult, however, because of the many different implementations that are possible and the conversion of the temporal spectrum to a multiply overlaid spatial spectrum.

An analysis of the noise spectrum resulting from DC restoration using a "hard clamp" shows that the noise power spectrum of the output of the clamp circuit is given by

$$S_{nDC}(f) = 2S_{nc}(f)\left[1 - \frac{\sin(2\pi fT)}{2\pi fT}\right] \qquad (17.)$$

where $S_{nc}(f)$ is the input noise power spectrum at the clamp point, $S_{DC}(f)$ is the output noise power spectrum, and T is the clamp period. This function is labeled "hard clamp" in Figure 4.

While this analysis correctly predicts the hard-clamped noise spectrum for a continuous video line, it is too pessimistic to be applied to TIS displayed imagery for two reasons. First, half of the high frequency noise power results from the hard clamping action, which adds the variance of the step function change in level which occurs at each clamp time to the noise power spectrum. When the video is displayed, the step function is not evident to an observer, nor is there any associated high spatial frequency noise power. The only evidence the observer has of the clamp is the varying brightness of the displayed line. Second, a well-designed system will not clamp to a single video sample, but rather to an average of many samples, thereby reducing the variance of the line-to line-brightness.

The function labeled "soft clamp approximation" in Figure 4 is an approximation to the filtering that results from a well-designed DC restoration function. This approximation retains the low frequency filtering effect of a hard clamp and the asymptotic approach to unity response at high frequency. The analytic function plotted is

$$MTF_c(f) = 1 + \left[\frac{(2\pi fT)^2}{15} - 1\right] e^{\left[-\frac{(2\pi fT)^2}{5}\right]} \qquad (18.)$$

3.2 NET Definitions

In first generations NS-TIS, it is customary to define NET in a standard way, and to measure it at a particular point in the (continuous) signal processing chain. This point is located just after a band limited amplifier, ahead of light emitting diodes or other display means. It has become customary to measure the noise at this point using a single-pole, low-pass filter with an upper half-power frequency equal to $(2\tau_d)^{-1}$, where τ_d is the time required to scan the image of a detector element past a point in the field of view.

This definition is inadequate for second generation S-TIS for several reasons. First, the data may already be in multiplexed format before any opportunity to measure the noise exists. Second, a well designed sampled data system will incorporate filters with a much sharper cutoff than that of a single pole filter. Finally, the noise bandwidth of a S-TIS is very likely to be quite different from the value for a single pole filter. For these reasons, it is suggested that additional NET definitions be given, each characterized by the point at which it is measured and the means used to measure it.

3.2.1 Pixel NET

The pixel NET is defined as the square root of the variance of a sequence of samples taken from the same detector element. If the data is in multiplexed format, the data must be demultiplexed at the measurement point so as to accumulate the statistics of each of the detector elements. For white noise, the noise bandwidth associated with this measurement, provided enough samples are analyzed, is just that of the amplifiers and filters used to condition the signal prior to sampling and multiplexing the data.

3.2.2 NET at the Display

Another useful NET definition is one modeled and measured at the input to the display. This measurement closely resembles the standard definition, since it can be made on the continuous data stream that results from reconstruction. No added filter should be use, however, since a well-designed TIS will employ adequate filtering prior to this point.

3.2.3 Cross-Scan NET

It has been suggested by CCNVEO that the cross-scan noise be measured in some manner as a measure of any fixed pattern noise that might have been inserted by the signal processing. To have any meaning, the noise would be measured by performing statistical analysis on the digitized samples from a number of different detector elements, after normalization of gain and level of these elements. The "cross scan rms noise" would be the square root of the variance of these samples. Sample averaging could be used to separate spatial noise from temporal noise as required to properly model the noise. See section 3.1.2 for a discussion of how such measurements should be correlated to cross-scan MRT.

3.3 MRT Definitions

Most first generation performance models use an MRT expression of the form

$$MRT(f_W) = k\, SNR_{th} \frac{NET}{MTF(f_W)} \left[\frac{SIF}{TIF} \right] \qquad (19.)$$

where f_W is the target fundamental spatial frequency, k is a constant, SNR_{th} is a threshold value for the perceived signal to noise ratio of the observer, SIF is a spatial and TIF a temporal integration factor attributed to the eye/brain of the human observer. My 1983 model, still in use, differs from other models only in the form of the spatial integration factor.

The NVL model uses the following form for the spatial noise integration factor (simplified):

$$SIF(f_W) = \left[\frac{v_\theta}{f_n S_{no}} \int_0^\infty S_n(f_x)[MTF_n(f_x) MTF_{eye}(f_x) H_W(f_x)]^2 df_x \right]^{1/2} \qquad (20.)$$

where v_θ is the object domain angular scan velocity, f_n is the noise bandwidth used to calculate NET, S_n is the noise power spectral density at the detector output, MTF_n is the transfer function of all sensor components following the detector, MTF_{eye} is the MTF of the eye, and

$$H_W(f_x) = \frac{\sin\left(\frac{\pi f_x}{2 f_W}\right)}{\frac{\pi f_x}{2 f_W}} \qquad (21.)$$

is the "matched filter function," taken to be the transform of the width of a single bar of the MRT target with fundamental spatial frequency f_W.