On Certain New Methodology for Reducing Sensor and Readout Electronics Circuitry Noise in Digital Domain

Semion Kizhner, Joseph Miko, Damon Bradley
National Aeronautics and Space Administration Goddard Space Flight Center
Semion.Kizhner-1@nasa.gov

Katherine Heinzen
University of Notre Dame

Abstract

NASA Hubble Space Telescope (HST) and upcoming cosmology science missions carry instruments with multiple focal planes populated with many large sensor detector arrays. These sensors are passively cooled to low temperatures for low-level light (L3) and near-infrared (NIR) signal detection, and the sensor readout electronics circuitry must perform at extremely low noise levels to enable new required science measurements. Because we are at the technological edge of enhanced performance for sensors and readout electronics circuitry, as determined by thermal noise level at given temperature in analog domain, we must find new ways of further compensating for the noise in the signal digital domain. To facilitate this new approach, state-of-the-art sensors are augmented at their array hardware boundaries by non-illuminated *reference pixels*, which can be used to reduce noise attributed to sensors. There are a few proposed methodologies of processing in the digital domain the information carried by reference pixels, as employed by the Hubble Space Telescope and the James Webb Space Telescope Projects. These methods involve using spatial and temporal statistical parameters derived from boundary reference pixel information to enhance the active (non-reference) pixel signals. To make a step beyond this heritage methodology, we apply the NASA-developed technology known as the Hilbert- Huang Transform Data Processing System (HHT-DPS) for reference pixel information processing and its utilization in reconfigurable hardware on-board a spaceflight instrument or post-processing on the ground. The methodology examines signal processing for a 2-D domain, in which high-variance components of the thermal noise are carried by both active and reference pixels, similar to that in processing of low-voltage differential signals and subtraction of a single analog reference pixel from all active pixels on the sensor. Heritage methods using the aforementioned statistical parameters in the digital domain (such as statistical averaging of the reference pixels themselves) zeroes out the high-variance components, and the counterpart components in the active pixels remain uncorrected. This paper describes how the new methodology was demonstrated through analysis of fast-varying noise components using the Hilbert-Huang Transform Data Processing System tool (HHT-DPS) developed at NASA and the high-level programming language MATLAB (Trademark of MathWorks Inc.), as well as alternative methods for correcting for the high-variance noise component, using an HgCdTe sensor data. The NASA Hubble Space Telescope data post-processing, as well as future deep-space cosmology projects' on-board instrument data processing from all the sensor channels, would benefit from this effort.

1. Introduction

For the vast majority of its existence, humanity has based its viewing knowledge on what can be seen with the naked eye (with perhaps some added magnification), thus relying on the visible portion of the electromagnetic spectrum. This band of radiation includes emissions with wavelengths ranging from 0.4 to 0.7 micrometers[1]. However, scientists have relatively recently discovered that many objects in nature – particularly distant, cosmic ones do not emit visible light – but can be "seen" or imaged through other portions of the electromagnetic spectrum. Hence, engineers have developed near-infrared sensors, which capture radiation with wavelengths varying from a little less than 1 micrometer to up to 5 micrometers[2]. NIR sensors allow scientists to image objects billions of light-years away that are emitting only faint radiation signals. The particular NIR sensor studied in this paper is manufactured by Teledyne Technologies, Inc., and is called the HAWAII-2RG (or H2RG) sensor, where the name stands for "**H**gCdTe **A**stronomy **W**ide **A**rea **I**nfrared **I**mager with **2**Kx2K resolution, **R**eference pixels and **G**uide Mode."[3] The H2RG sensor – made of a mercury-cadmium-telluride (HgCdTe) substrate – is bonded to a multiplexer, which is connected to an application-specific integrated circuit (ASIC), specifically Teledyne's SIDECAR ASIC (where SIDECAR stands for "system image, digitizing, enhancing, controlling, and retrieving"[4]). The multiplexer condenses the massive analog readout from the four million sensor array pixels into a much more manageable number of output channels (ranging from 1 to 32) and allows readout at different time rates. The ASIC controls the sensor, reads out the analog signals from the sensor, and it digitizes these signals. This data is then transmitted to a Field Programmable Gate Array(s) (FPGA) for data processing and storage under the control of an FPGA-imbedded or general-purpose on-board instrument computer(s). New challenge in signal-to-noise (SN) ratio control arises when sensor measurements are read out on the maximum number of the sensor channels (32 for H2RG), as opposed to channels 1-4, used by heritage projects.

In keeping with the cutting-edge nature of these sensors, NIR detector arrays are furnished with *reference pixels that are read-out in the same way as the measuring ("hot") pixels.* The reference pixels, built into the sensors, do not actually register the radiation that is illuminating the arrays. Instead, reference pixels measure the noise incurred on the arrays due to a variety of sources. These reference pixels are a type of noise-correction technology for the digital domain, in addition to a single analog reference pixel subtracted from all hot pixels on the sensor. That is, rather than try to prevent noise from occurring by improving the quality of sensor components – an approach limited by costs and physics – scientists and engineers frequently seek to correct data after it has been recorded and converted from analog to digital signals, i.e. when it is in the digital domain. One key type of noise measured by reference pixels is thermal noise, or the random motion of electrons inherent in all objects at temperatures above absolute zero (0 Kelvin). While most other types of noise can be minimized in the analog domain at component fabrication, thermal noise is extremely difficult to take out without engaging in expensive cryogenic procedures. Thus, noise of thermal variety is best dealt with in the digital domain. Furthermore, in the course of heritage-method averaging in the digital domain, the fast-varying noise components, which can be modeled by sinusoids varying around zero, drop out from noise

[1] "Electromagnetic Spectrum"
[2] "Near, Mid and Far-Infrared"
[3] HAWAII-2RG Technical Documentation.
[4] "SIDECAR™ ASIC"

reduction calculations and remain hidden in the readout data. Thus, enhanced digital domain noise reduction techniques could be of great benefit to the scientific community. An increase in the accuracy of sensor readouts by even a few percent would greatly improve scientists' ability to qualify NIR sensors for use in space.

Through a series of algorithms run from MATLAB language scripts, we have tested the hypothesis that heritage methods fail to compensate for fast-varying noise components present in the data. After these evaluations, HHT-DPS was used to analyze the noise components in an actual data file, and experiments were run to determine the impact, if any, of the fast-varying noise components. Finally, programs were written, testing the improved noise-reduction proposition on both simulated and actual sensor data.

1.1 Hypothesis

Heritage methods of noise reduction using reference pixels, such as subtraction of global statistics, overlook fast-varying noise components present in the data. An improved method using the HHT-DPS tool, which breaks down vector functions into their data-derived basis functions, can help identify and eliminate this fast-varying noise using an algorithm based on the propagation of heat in a thermal model. Following this, the heritage subtraction method can evaluate and compensate for statistical trends in slower-varying noise components.

1.2 Fundamentals of Thermodynamics

"Thermodynamics is the study of the effects of work, heat, and energy on a system."[5] Discussion of thermodynamics in this report focuses on noise sources, particularly the thermal variety (the noise due to random particle motion within sensors and their accompanying electronics). Thermal noise is attributable to heat, or thermal energy. "Heat IS thermal energy. It is the energy associated with molecular motion, including translation, vibration, and rotation."[6] Heat is also often described as "the transfer or flow of energy from a hot object to one that is cooler."[7] In the vacuum of outer space, heat is transferred primarily through radiation, where electromagnetic waves carry thermal energy without needing a medium through which to travel. In space, heat can also occasionally be transferred through conduction, in which molecules that are touching transfer thermal energy to and through each other. The sensors and their readout electronics studied in this project experience thermal noise through radiation from cosmic bodies and through conduction by contact with each other.

Accompanying the study of thermal energy and heat transfer are the laws of thermodynamics. This paper focused on thermal noise phenomena due to the first and third laws of thermodynamics. The first law states that energy is neither created nor destroyed but merely changes form; i.e. some electrical energy from the sensor and its boundary hardware components contribute to the overall heat (thermal energy) of the sensor, some of which is recorded as thermal noise in the reference pixels. In a close system the internal energy is a state variable, just like the temperature or the pressure. The first law of thermodynamics defines the internal energy (E) as equal to the difference of the heat transfer (Q) into a system and the work (W) done by the system. The third law describes the state of absolute zero as being the absence of kinetic energy

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[5] "What is Thermodynamics?"
[6] "Heat and Thermal Energy"
[7] "Energy Rules!: Section B. Energy Transfer"

(also called thermal motion) in the molecules of a given body.[8] Any objects not in this state – that is, at a temperature above absolute zero – experience thermal noise. It states that "it is impossible by any procedure, no matter how idealized, to reduce any system to the absolute zero of temperature in a finite number of operations". Improved digital domain noise reduction techniques will help account for this ubiquitous type of noise.

1.3 Background to HHT-DPS

The Hilbert-Huang Transform Data Processing System is a computer software program that employs the Empirical Mode Decomposition (EMD) algorithm to break down any given function into its basis function components. These components are called Intrinsic Mode Functions or IMFs. IMFs are formed through sifting and splining (interpolation) processes in the algorithm which produce functions having "more than 3 extrema points, and the difference of the number of extrema and zero-crossings is not more than 1."[9] Each newly formed IMF is subtracted from the input vector to form the next function for sifting and splining.

2. Methodology

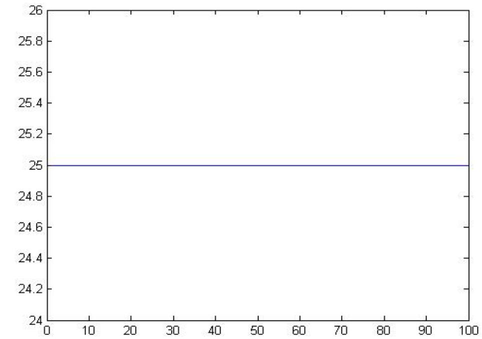
We first attempted to use the heritage methods for reducing noise in MATLAB-simulated images by directly taking out the fast-varying component. Although several programs were written and tested, only a few of the most significant programs are described here. These programs were critical in verifying the hypothesis. In addition, the solution methodology is described in detail. This includes using HHT-DPS to identify the fast-varying noise component, creating a correction-value matrix based on that component, subtracting the matrix from the active pixel data, and using the heritage method to subtract the average of the remaining noise components from the sensor data. Note: the terms "fast-varying noise component," "first IMF," and "IMF1" all refer to the same entity. This is an important distinction for the remainder of the paper.

2.1 Fast-Varying IMFs

Early attempts at subtracting the first, fast-varying IMF in various configurations – such as across columns or down rows – from noise matrices proved ineffective. These programs were meant to observe if using the first IMF, obtained from HHT-DPS, in a data-correction technique made any substantial impact on noise reduction, since a key facet of the hypothesis is that the fast-varying IMF causes problems that heritage methods cannot fix. However, the poor results of these MATLAB scripts demonstrated that simplistic subtraction of IMF1 from matrices was an ill-conceived approach.

Based on the unsatisfactory outcomes from previous programs using two-dimensional matrices, we turned to a more straightforward approach: the image is a constant-value vector, and sinusoidal noise is applied to it. Then, this entire vector is analyzed using HHT-DPS, and the first IMF is read back into MATLAB and subtracted from the noise vector. The images below (Figures 1 through 4) display the encouraging results. Although the final image is not linear, its sinusoidal variations have amplitude of only about 0.0004 units; thus, the final image can be considered approximately linear when viewed on a scale with increments in the tenths of a unit.

[8] "Laws of Thermodynamics"
[9] "On Certain Theoretical Developments Underlying the Hilbert-Huang Transform"



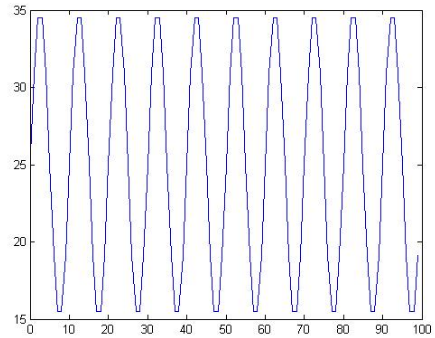
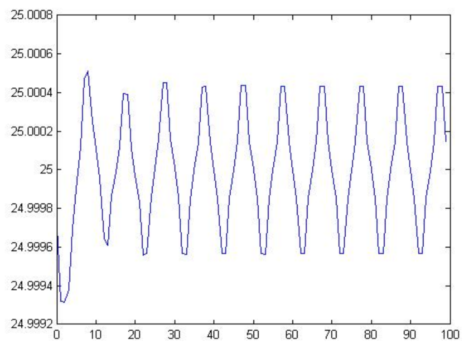


Figure 1. Original Vector Plot. **Figure 2. Noise Plot.**



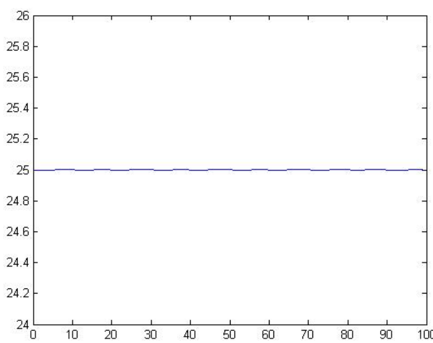
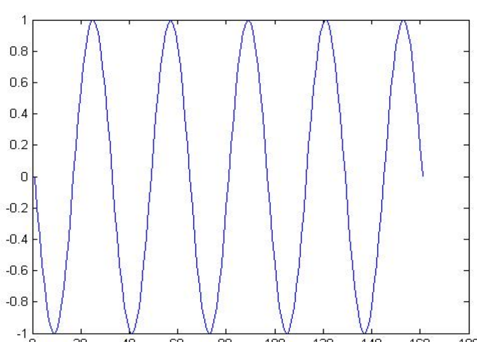


Figure 3. Final Plot after Noise Reduction **Figure 4. Final Plot Zoomed Out**
***Note the small amplitude**

Another successful attempt resulted from a simple correction using the first IMF. This program employs the same ideas as the previous program of a vector-oriented original image to which sinusoidal noise is added; however, the key change in this program is that the original image is also sinusoidal. This modification models the analog data that sensors receive in space. When the noise vector was broken down in HHT-DPS (Figure 6) and the fast-varying IMF was subtracted from the noise vector, the plot of the final vector was the same as that of the original image, with the exception of a slight vertical compression of 0.1 units (Figures 5 and 7).



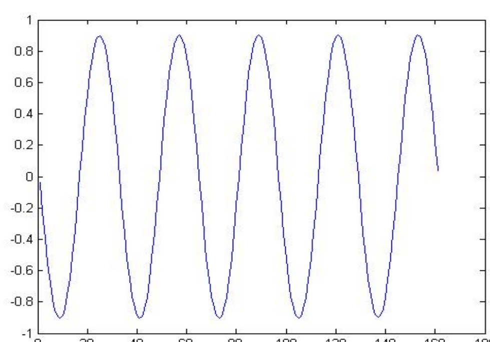


Figure 5. Original Plot **Figure 7. Final Plot**

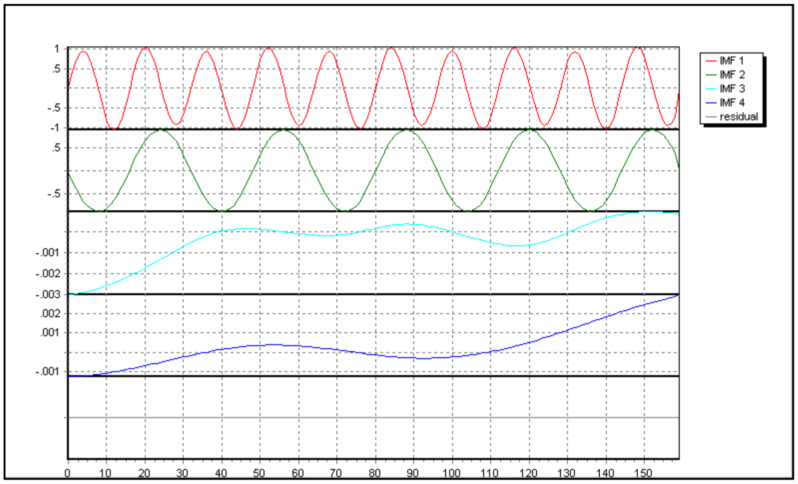


Figure 6. HHT-DPS Analysis of Noise Vector

While the successes were encouraging, both of these programs subtracted the fast-varying noise component from *all* the vector data, since there was no segment analogous to reference pixels. In practice, the first IMF would only be subtracted from the active pixel data. However, if one were to view the programs' noise vectors as simulations of reference pixel data pervaded by noise, then the results would represent a returning of the reference pixel vector to its pre-noise state (which in reality is hoped to be near zero).

2.2 Hypothesis Testing

Based on the programs described above – which show the probable impact of the first, fast-varying IMF – and on the following analysis, we have demonstrated the hypothesis to be valid. The hypothesis states that a significant section of sensor readout noise is comprised of at least one fast-varying component. This portion of noise is averaged out and thus ignored using heritage global statistic subtractions, but it is still physically present in the signal and continues to disrupt the clarity of the image. In order to test this proposition, we wrote a MATLAB program that examines one of the FITS-format sample data files from a HAWAII-2RG sensor. (This file was obtained from the GSFC Detector Characterization Lab, or DCL.) The file consists of 2Kx2K data in four layers, with each layer corresponding to a pixel array on the sensor. The program, which only examined the second layer, revealed that the global mean of all the reference pixel data was a value on an order of magnitude of 10^5. Then, each reference pixel row and column in the layer was isolated and analyzed using the HHT-DPS software, after which the IMF files were read back into MATLAB. For each row and column analyzed in HHT-DPS, the mean of the first, fast-varying IMF was taken, as was the mean of the absolute value of the first IMF. In every case, the mean of the absolute value was at least one order of magnitude higher than the simple mean. These results demonstrate that, if the absolute value were not taken into account, the mean of the fast-varying IMF would nearly average out to zero. Therefore, this finding reveals that heritage methods are indeed ignoring a component of noise that could have a significant effect on the overall noise. Equation Set 1 shows the generic formulas for the means calculated in MATLAB, and Tables 1 and 2 present the above analysis numerically.

Signal 1 (Reference Pixel Vector): $s = \{s_1, s_2, \ldots, s_n\}$

Mean: $\mu_0 = (\sum s_i)/n,\ 1 <= i <= n$

Signal 2 (IMF1): $r = \{r_1, r_2, \ldots, r_n\}$

Mean: $\mu_1 = (\sum r_i)/n,\ 1 <= i <= n;$

$\mu_{1ABS} = (\sum |r_i|)/n,\ 1 <= i <= n$

Equation Set 1. General Formula for MATLAB Calculation of Averages

Table 1. Reference Pixel Row 4 IMF Mean Analysis

Reference Pixel Row 4		% of μ_0
μ_0: Mean of Row 4	10881	100.00
Mean of Absolute Value of Row 4	10881	100.00
μ_1: Mean of IMF1	2.7708	0.03
Mean of Absolute Value of IMF1	798.4533	7.34

Table 2. Reference Pixel Column 4 IMF Mean Analysis

Reference Pixel Column 4		% of μ_0
μ_0: Mean of Column 4	20289	100.00
Mean of Absolute Value of Column 4	20289	100.00
μ_1: Mean of IMF1	40.9726	0.20
Mean of Absolute Value of IMF1	703.8634	3.47

It is important to note, however, that while most of these evaluations examined the effect of using the absolute value of sinusoidal functions, absolute value is just one example of a method to account for the effects of fast-varying noise components. Other methods of determining and accounting for the impact of fast-varying noise components exist and should be investigated.

2.3 The Thermal Model Methodology

Once the hypothesis was demonstrated to be valid, it was necessary to determine how to proceed with the information gleaned from the verification of the hypothesis; namely, that there is a fast-varying noise component, this component does contribute significantly to the overall noise, and heritage noise reduction methods overlook this component. First, my mentor had me investigate a model for diffusion of heat across a small, thin square plate on the NetLogo Models Library website. The purpose of investigating this heat diffusion model was to see if it would provide a suitable algorithm for propagation of noise across an NIR sensor, in large part because the small, thin square plate typifies modern sensors. The model allows the user to select boundary temperatures and the initial plate temperature. The user may also select the plate material, since this affects the plate's thermal diffusivity (the speed with which heat propagates through a substance, represented by the "alpha" sliding bar on the left-hand side of the screen captures below). After examining the model in operation in several different temperature scenarios, the heat distribution technique appeared to be applicable to this project. Below are the algorithm provided by the website and pictorial examples of the model in operation (Figure 8). [10]

2.3.1 Algorithm Outline

"Initialize the plate and edges to have temperatures that equal their respective slider values. Each time through the GO procedure, diffuse the heat on each patch in the following way. Have each patch set its current temperature to the sum of the 4 neighbors' old temperature times a constant based on alpha plus a weighted version of the patch's old temperature. (For those interested, the updated temperature is calculated by using a Forward Euler Method.) Then the edges are set back to the specified values and the old temperature is updated to the current temperature. Then the plate is redrawn."[11]

Screen Capture with Initial Plate Temperature = 1, Temperature = 100 on all edges

Beginning: *Middle*: *End*:

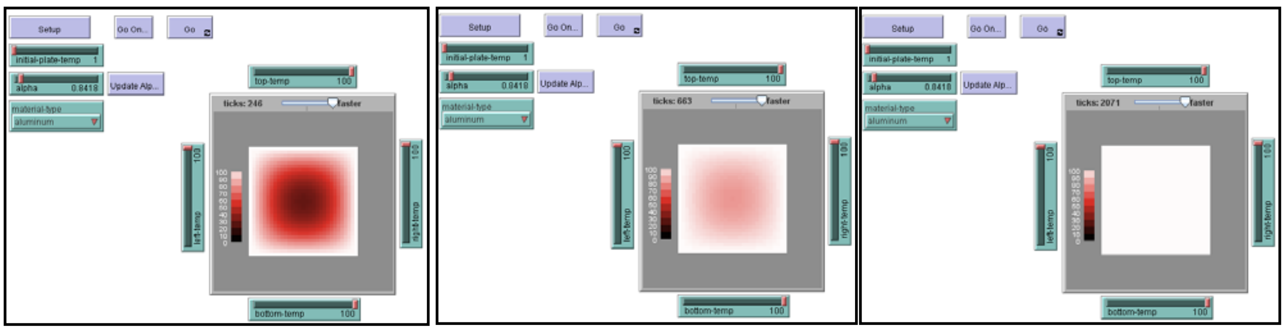


Figure 8. Pictorial Representation of Heat Diffusion Model

The NetLogo thermal model was a key aid in determining how noise recorded on the reference pixels propagates across the active pixels. This NetLogo model may or may not be the best option for simulating noise propagation, but it nonetheless gave us an established reference point from which to develop a propagation technique.

2.4 Solution Methodology

After we determined that the model would be useful, my mentor explained to me our general solution methodology:

1) use HHT-DPS to find the IMFs of a reference pixel vector;
2) apply μ_1 – the correction value matrix for fast-varying IMF1 – using the thermal model for a square and subtracting this matrix from the active pixels;
3) find μ_2 – a single value – by averaging all the IMFs, with the exception of IMF1;
4) apply μ_2 in the heritage way (subtraction from the active pixels).

To elaborate, this approach to noise reduction uses HHT-DPS to identify the first, fast-varying IMFs of the innermost rows and columns of reference pixels; that is, the rows and columns adjacent to the active pixels, numbered 4 and 2045. (Note: the first several IMFs may be fast-

[10] NetLogo Heat Diffusion Model
[11] ibid

varying and should eventually be accounted for, but for the sake of simplicity this project's methodology only considered the first IMF.) The mean of the absolute value of each first IMF was taken, and these IMF1 mean values formed the corresponding row and column boundaries of the correction-value matrix that was ultimately subtracted from the active pixel data.

Two different techniques were used to distribute the reference pixel noise values across the remainder of the correction-value matrix. Our program (MATLAB script) ThermalModelVerification.m (hereafter TMV) tested the general approach, as outlined above, for the solution methodology. TMV uses fabricated reference pixel data for the edges of the correction matrix, and it propagates this data in a four-quadrant pattern: across the rows and up or down the columns, as necessary, so that the numbers decrease from all directions as they reach the middle of the matrix. The following surface plot (Figure 9) is the result of executing the program. The upside-down cone shape was expected, and it thus indicates that the program correctly executed the desired algorithm.

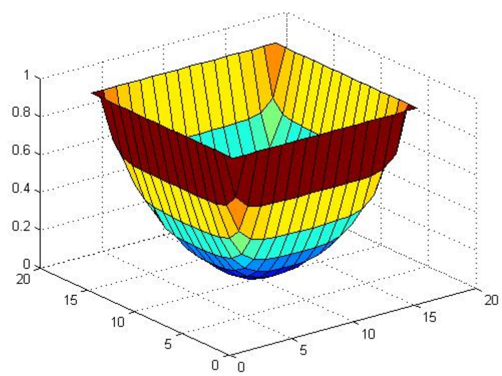


Figure 9. Surface plot of TMV correction-value matrix.

The final noise-reduction program uses the first, fast-varying IMFs from each of the innermost reference pixel columns and rows from a HAWAII-2RG sensor sample file. These IMFs form the boundaries of a correction-value matrix the size of the active pixel region of the data sample. Some modifications were made to the propagation algorithm to account for undesirable effects resulting from the use of the TMV algorithm. When that method was implemented in this new program, the inner values of the matrix moved to zero so quickly that much of the center of the matrix held the value of zero. This seemed to be at odds with the purpose of subtracting IMF1 noise from the active pixel data, so my mentor suggested another approach, which we then enacted. The IMF1 data now propagates across the inner region of the correction-value matrix through a pattern of embedded squares, beginning with the boundary square of IMF1 data and moving inward toward the center of the matrix. Once established, this matrix (Figure 10) is subtracted from the active pixel data. Then, the remaining IMFs from each of the innermost reference pixel vectors are added up, the means of the groups of remaining row/column IMFs are determined, and the overall mean is calculated by taking the mean of the IMF averages. Finally, this global statistic is subtracted from each of the active pixels.

The result is the final data, with the noise newly reduced.

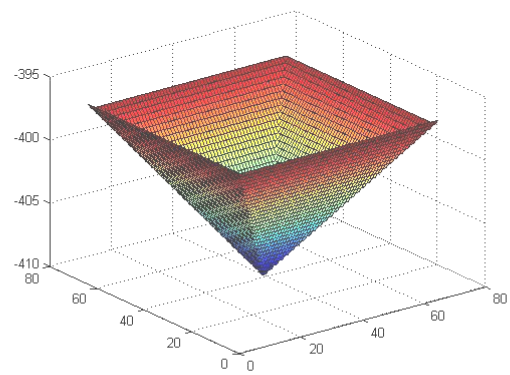


Figure 10. Surface plot of the central portion of the final TMV correction-value matrix.

Conclusions

Based on the research outlined above, this paper presents an enhanced method for reducing noise in sensors equipped with reference pixels. The thermal model inspired the quadrant and embedded squares propagation techniques, which can compensate for fast-varying noise components, while the heritage methods provide a global mean for subtracting slower-varying noise components from the data. However, as with any new finding, the methodology needs more thorough testing on a wider variety of sensors and data than was allowed for by the limited research time of summer. For example, though the above graphic (Figure 10) shows the algorithm to be operating correctly, the solution methodology should be tested on sample data where the initial image is known. This would allow one to determine if the image returned after using this noise reduction technique is similar to the original image, and therefore whether the technique is effective. In addition, a process must be found that allows more than the first fast-varying IMF to be accounted for, since most reference pixel vectors will contain multiple fast-varying IMFs. Furthermore, my MATLAB script solution is only one approach for incorporating the thermal model and heritage techniques into a single program for noise reduction. Additional research should be performed to investigate other ways of integrating this methodology into a computer program. For wider applicability, the ultimate program intended for scientific and commercial use should be written in a language compatible with more computing systems, such as C++ or any other suitable platform.

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Semion Kizhner, Joseph Miko, Damon Bradley

NASA-Goddard Space Flight Center

Semion.Kizhner-1@nasa.gov

National Aeronautics and Space Administration

Katherine Heinzen

University of Notre Dame

Introduction
Sensors and Noise

- New sensors: near-infrared (NIR), wavelengths ~ 1 to 5 μm (Figure 1), “active” or “hot” pixel arrays capture image data
- Array is 2048 by 2048 pixels (2Kx2K>4×10^6 pixels, K=1024)
- Active pixel arrays are bounded by reference pixels, which measure noise (4 columns and 4 rows on the left-right and top-bottom sides of the array). Figure 1 depicts the **H**gCdTe **A**stronomy **W**ide **A**rea **I**nfrared Imager (HAWAII) with (**2**K-8)x(2K-8) hot pixel resolution, **R**eference pixels and **G**uide Mode (or **H2RG** sensor).
- Noise: readout error due to several sources, including background radiation and movement of electrons (thermal noise)

Introduction
Sensors and Noise
(Continue)

- Thermal noise effects are unavoidable in objects at temperatures above absolute zero (0 Kelvin)

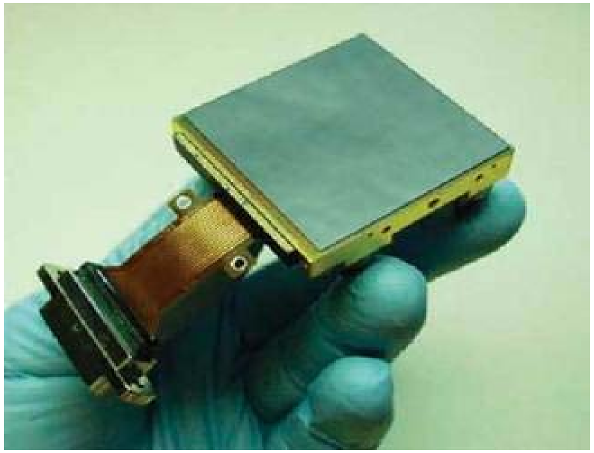
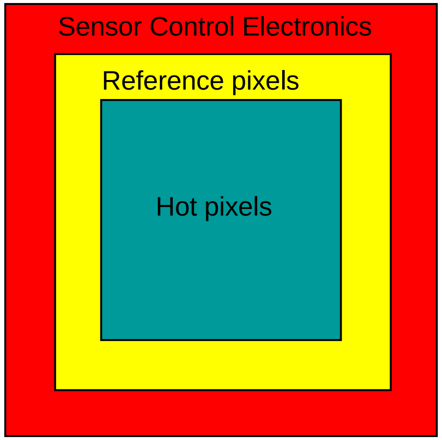


Figure 1. HAWAII-2RG NIR sensor.
Source: www.laserfocusworld.com



Heritage Noise Reduction Methods in Digital Domain

- Heritage Global Statistics Subtraction: Summarize reference (noise) pixels with a statistical parameter, such as the mean of all reference pixels, and subtract this single parameter from all active pixel data
- Heritage approach unintentionally ignores fast-varying noise components, which average out to zero.

Problem and Solution Hypothesis

Problem:

- Heritage noise reduction methods in digital domain do not give required measurement precision
- Certain key components of noise are unintentionally ignored by heritage approach for large detector arrays such as the H2RG

Solution Hypothesis:

- Heritage methods overlook fast-varying noise components in data
- Improved method: use HHT-DPS to identify and account for these components

Solution Tools

HHT-DPS:

- Hilbert-Huang Transform Data Processing System (HHT-DPS): software that breaks down any function into the data-derived basis functions that comprise it (Figure 2):

Intrinsic Mode Functions (IMFs)

Figure 2. Sample HHT-DPS IMF breakdown of a reference pixel column

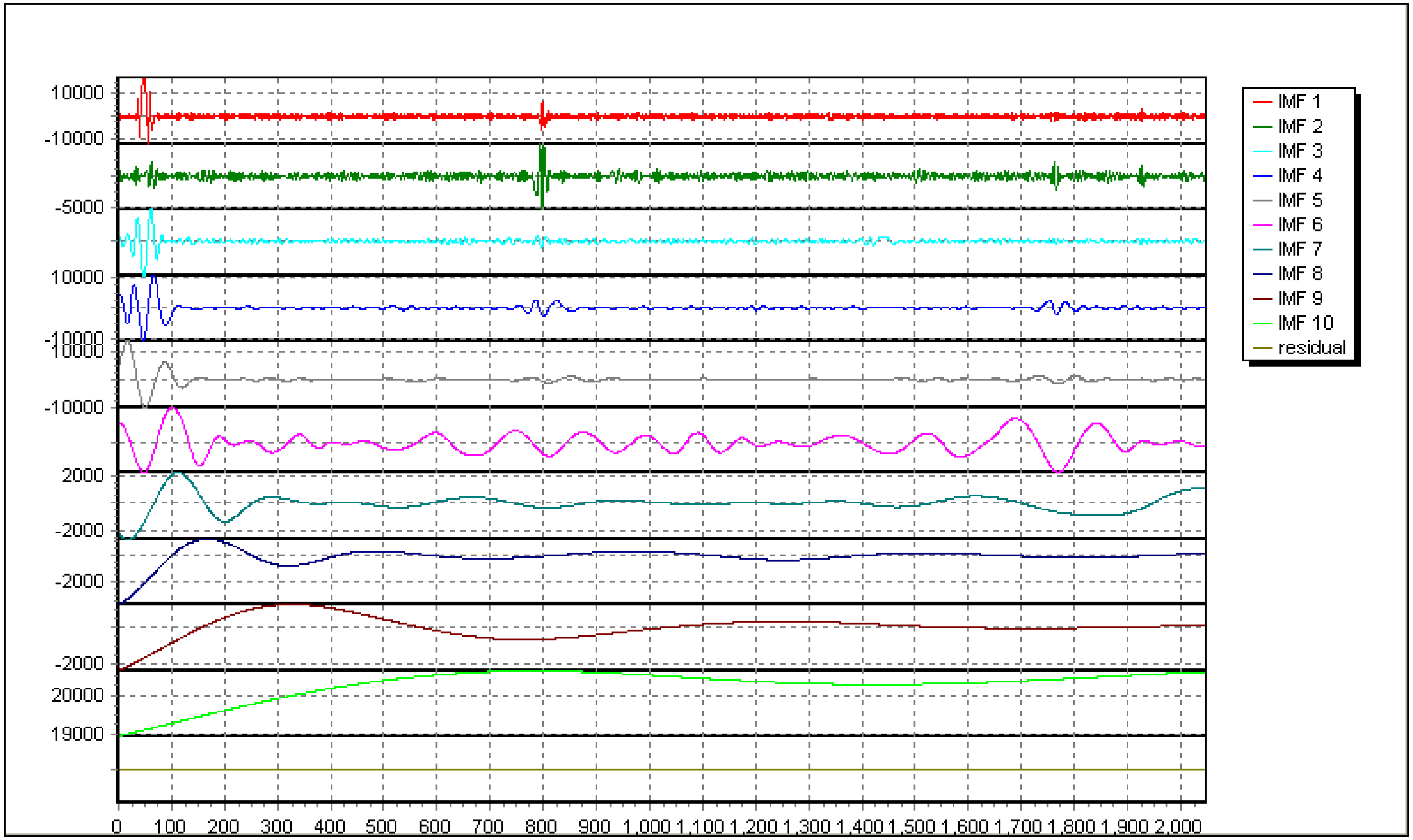


Figure 3

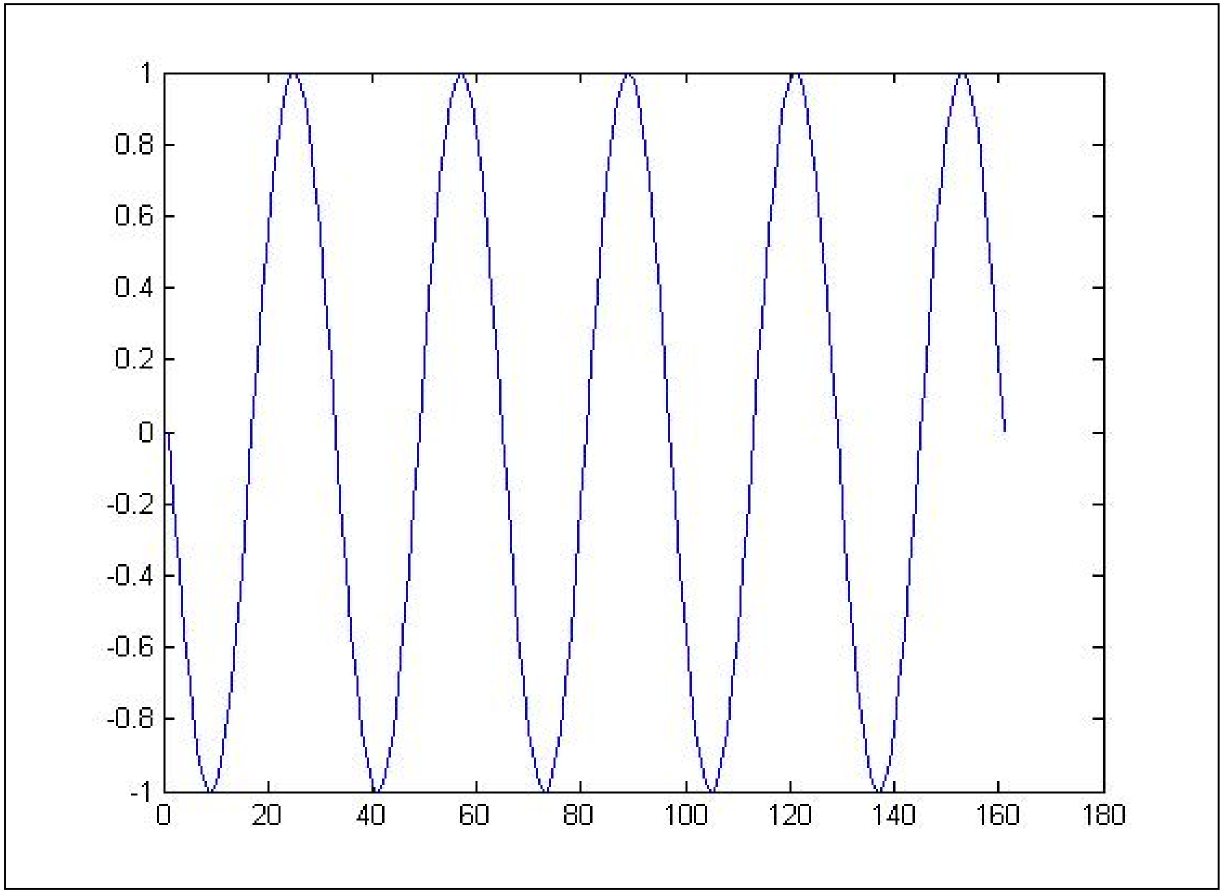
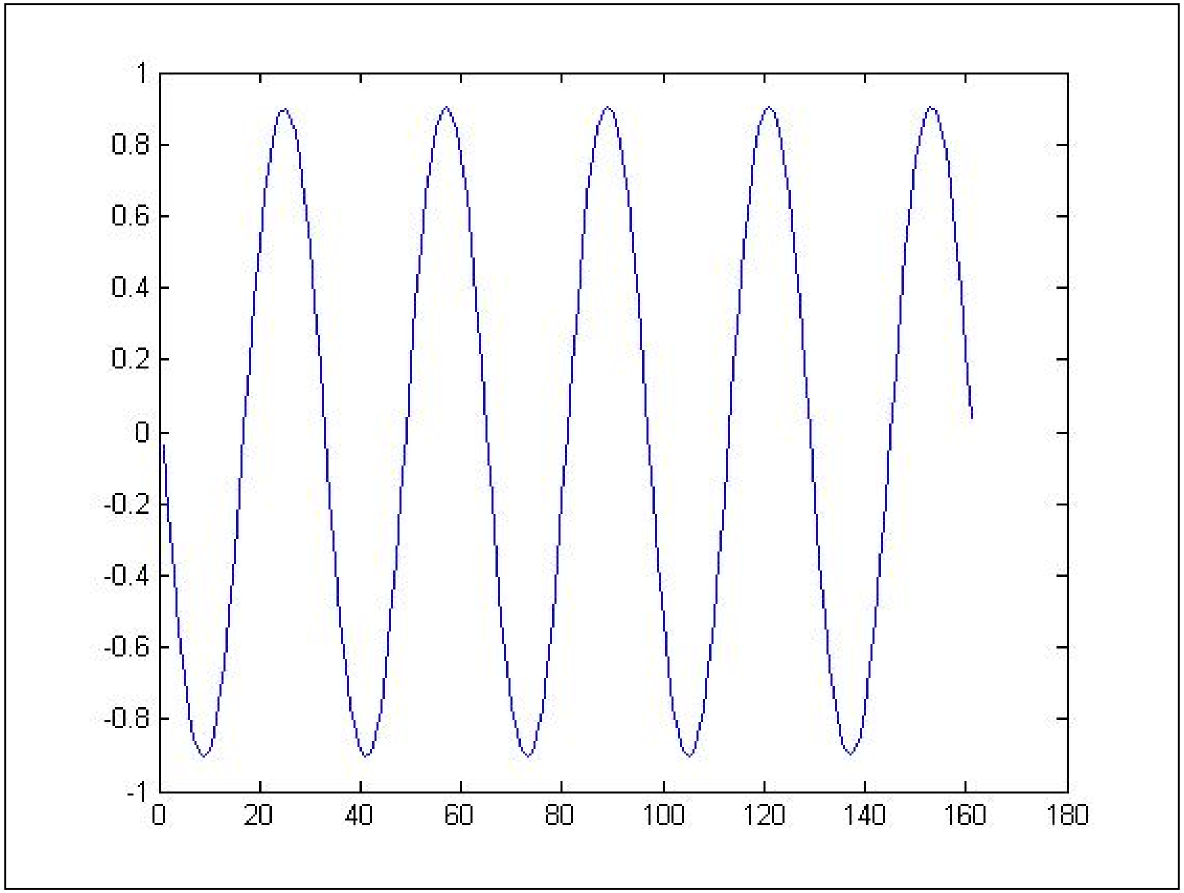


Figure 4



Statistical Parameters' Equations and Table 1

Signal 1 (Reference Pixel Row): $s = \{s_1, s_2, \ldots, s_n\}$

Mean: $\mu_0 = (\Sigma\ s_i)/n,\ 1 <= i <= n$

Signal 2 (IMF1): $r = \{r_1, r_2, \ldots, r_n\}$

Mean: $\mu_1 = (\Sigma\ r_i)/n,\ 1 <= i <= n$; $\mu_{1ABS} = (\Sigma\ |r_i|)/n,\ 1 <= i <= n$

Ref. Pixel Row 4		% of Mu0
Mu0 (Total Mean of Row)	10881	100
Mean of Abs. Value of Row	10881	100
Mu1 (Mean of IMF1)	2.7708	0.03
Mean of Abs. Value of IMF1	798.453	7.34

New Proposed Methodology

- Use both, the HHT-DPS/thermal model correction for noise fast varying components algorithm and the heritage statistical parameter subtraction method for low varying noise components

- Thermal model: take out fast-varying noise (HHT-DPS first IMF)

- Heritage method: statistically average the remaining IMFs and subtract average from all hot pixels.

Thermal Model Analogy for Noise Propagation

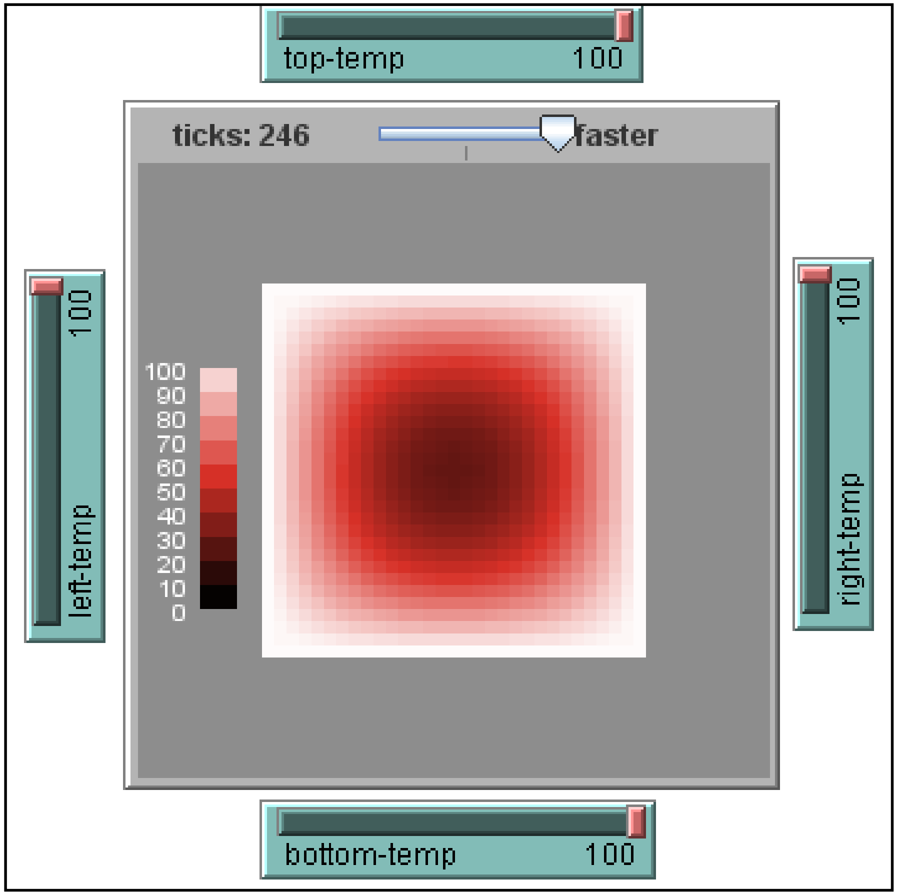
- In-time progression of diffusion of heat across a small, thin square plate (Figure 5)

  Source: NetLogo Models Library website

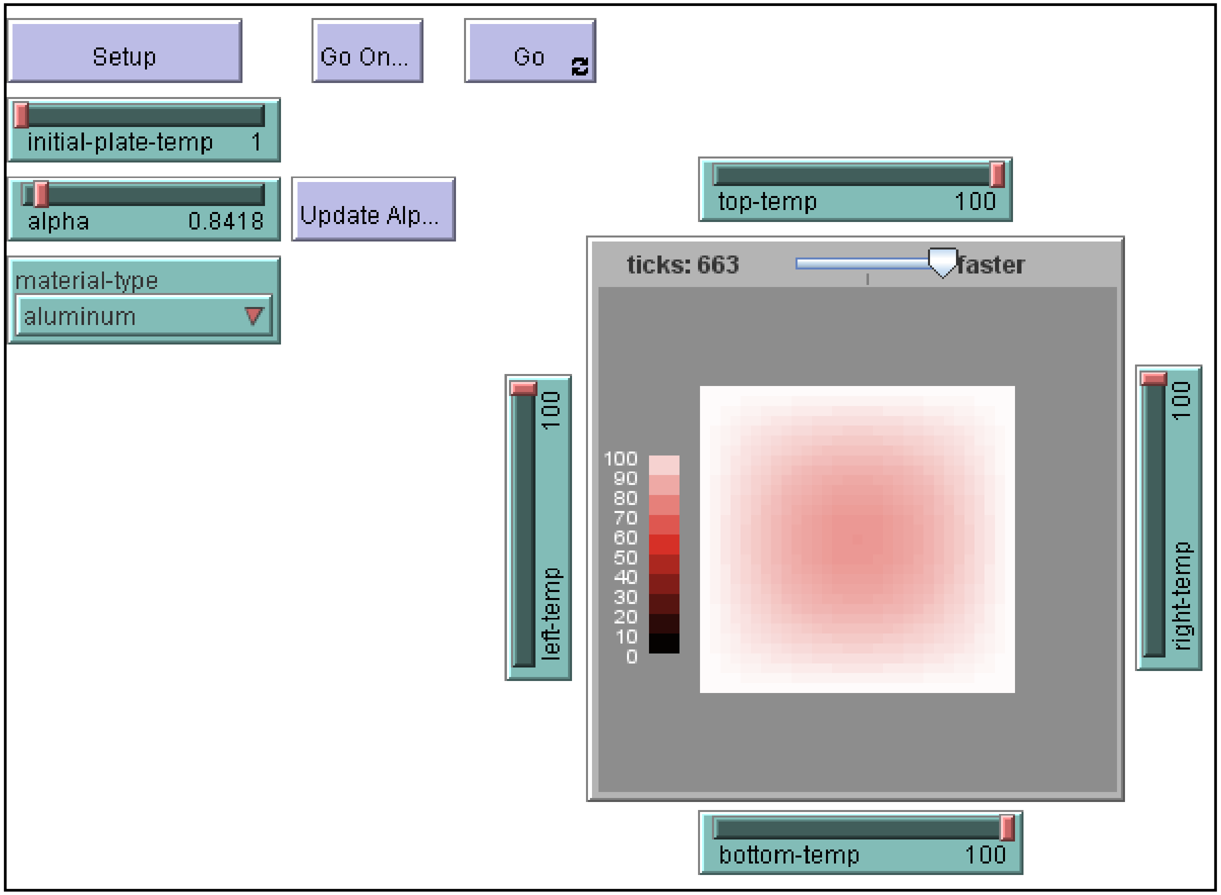
- Variable temperature settings along edges analogous to reference pixel values

- Simulates propagation of thermal noise in NIR sensor

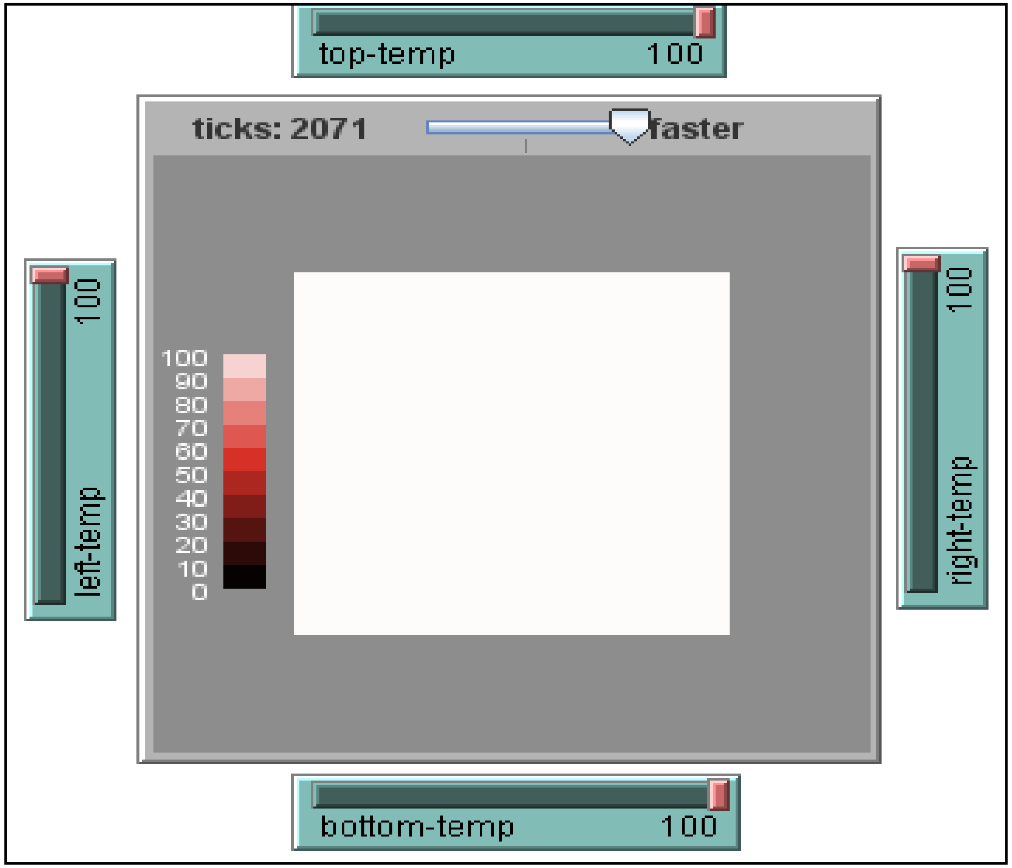
Beginning Thermal Configuration



Middle Thermal State



End Thermal State



Algorithm Outline

- Use sample binary data file in FITS format from an H2RG HgCdTe NIR sensor; read file into MATLAB (Trademark Of MathWorks Inc.) array
- Use HHT-DPS to decompose innermost reference pixel rows/columns into IMFs
- Find noise matrix due to first IMFs using thermal model :

*Calculate mean of first-IMF for each decomposed reference pixel row/column: this is the value for the corresponding boundary row/column of noise array

*Divide maximum of these means by number of values in the total array (2042) = initial value of all noise

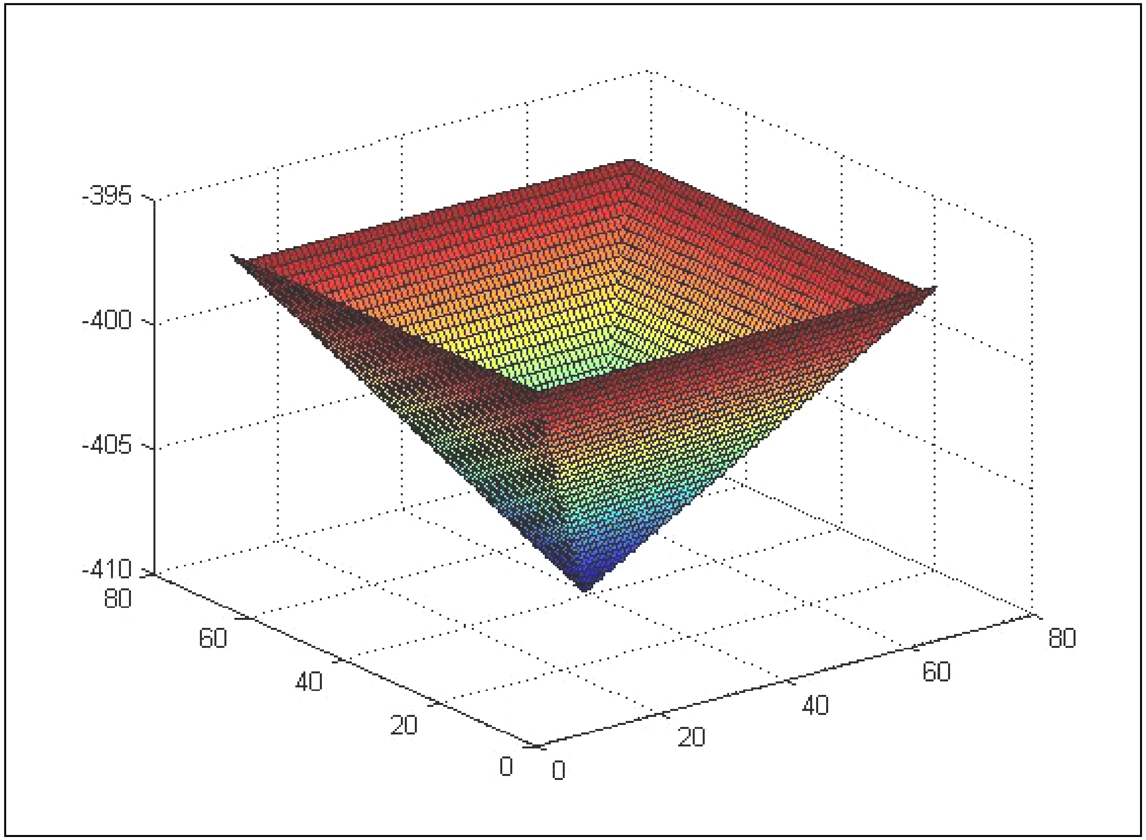
Algorithm Outline (Continue)

*Propagate first-IMF noise using embedded squares:

starting with boundaries, calculate matrix values by moving inward, forming ever-smaller squares (Figure 6)

- Subtract resulting first-IMF noise matrix from active pixels
- Average remaining IMFs for each innermost reference pixel row/column, then average all these means=global mean
- Subtract this global average from active pixels that are already corrected for first-IMF error
- Subtract resulting first-IMF noise matrix from active pixels

Figure 6. Result of Thermal Model Analogue for Noise Propagation



Conclusions and Acknowledgements

Conclusions:

- Method appears effective
- Further testing and refinement of methodology is needed

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