Removing Spikes While Preserving Data and Noise using Wavelet Filter Banks

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Abstract—Many diagnostic datasets suffer from the adverse effects of spikes that are embedded in data and noise. For example, this is true for electrical power system data where the switches, relays, and inverters are major contributors to these effects. Spikes are mostly harmful to the analysis of data in that they throw off real-time detection of abnormal conditions, and classification of faults. Since noise and spikes are mixed together and embedded within the data, removal of the unwanted signals from the data is not always easy and may result in losing the integrity of the information carried by the data. Additionally, in some applications noise and spikes need to be filtered independently. The proposed algorithm is a multi-resolution filtering approach based on Haar wavelets that is capable of removing spikes while incurring insignificant damage to other data. In particular, noise in the data, which is a useful indicator that a sensor is healthy and not stuck, can be preserved using our approach. Presented here is the theoretical background with some examples from a realistic testbed.[1 2]

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1. INTRODUCTION

Interference and unwanted currents or voltages in an electrical device or system create noise; whereas, spikes are usually a result of quick transitions in the electrical circuit equilibrium. Examples include switching and relaying operation in power grid networks, current and voltage inversions, short-circuits, lightning, and discharge of inductive or capacitive loads. Despite the short time-span of spikes compared to the steady state of the circuit, or the low amplitude of noise compared to the entire signal, they can affect the circuit analysis immensely.

A new approach, based on wavelets, to suppress spikes and preserve noise is presented in this paper. The approach is motivated by computational methods for diagnostics and is illustrated using electrical power system data obtained from ADAPT (Advanced Diagnostics and Prognostics Testbed) as shown in figures 1 and 2 [8, 9]. The probabilistic model in this study is a Bayesian network (BN) [4-7]. As shown in figure 1, the proposed filtering approach sits in between the plant and diagnoser. It has to act on the raw data before the data is processed for diagnosis. The "de-spiked" data serves two purposes: 1) the diagnoser uses the noise to determine the health of the sensors and 2) the data is used to realize the overall state of the system and to calculate the probability of any faults occurring.

In this research, data from a real-world diagnostic platform, namely ADAPT at NASA Ames, have been used in a graphical model (based on Bayesian network, BN) in conjunction with the proposed digital filter (discrete Haar wavelet) algorithm [1-3, 16, 17]. The research presented in this paper is an effort to further optimize the diagnostics approaches by applying advanced signal processing algorithms for noise preservation and spike removal. Using the multi-resolution and multi-orientation properties of digital signal processing (DSP) such as Haar Wavelet Filters, datasets can be decomposed into their components. Spikes embedded in the data (and noise) can be manipulated in advance of the probabilistic diagnostics using BNs.

Generally, for most physical systems, spike removal and de-noising are both beneficial to diagnosis. For certain systems, such as ADAPT EPS, noise may be used as an indication for sensor health where a sensor could be stuck at a particular value with no noise. Spike (outlier) and noise removal are both fairly old disciplines. In most of previous approaches either noise or spike has been removed from data while affecting the other parameter. The significance of this work is in its approach to make this process selective by means of customized wavelet transform filters and addition of translation and scale invariance to make threshold adjustable.

Spike could also carry some diagnostic information. Spikes are necessary for detection of intermittent events such as short circuits or arcs caused by lightning. Removal of spikes or other signatures that are noticeable only in the transient

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response would be detrimental to diagnosis in these cases. Additionally, one should be able to extract information such as time of occurrence from spikes. The new set of filters presented here are capable of removing spikes that are anomalies to dataset without interfering with transient response. Furthermore, the threshold adjustment feature allows for replacing the spikes with data points that are very close to real data values at a given point.

In section 2 of the paper, the need for a new approach in signal processing to differentiate between noise and spike in a dataset has been explained. Then formulation for the proposed approach has been summarized. Section 3 describes the method in which the proposed algorithms are applied to the ADAPT EPS dataset. In section 4, we have detailed the experimental settings for this research. Section 5 of the paper consists of the concluding remarks and a series of experiments proposed for future work in this research field.

2. PRELIMINARIES

Traditionally, Fourier transform (FT) has been applied to time-domain signals to analyze them for normal behavior and signatures of transient response. The shortcoming of the FT is in its dependence on time averaging over entire duration of the signal. Due to its short time span, spike analysis requires resolution in particular time and frequency rather than frequency alone. Wavelets can help processing in this respect. Wavelets are the result of translation and scaling of a finite-length waveform known as a mother wavelet. A wavelet divides a function into its frequency components such that its resolution matches the frequency scale and translation. To represent a signal in this fashion it would have to go through a wavelet transform. Application of the wavelet transform to a function results in a set of orthogonal basis functions which are the time-frequency components of the signal. Due to its resolution in both time and frequency, the wavelet transform is a powerful tool for detection and classification of signals that are non-stationary or have discontinuities and sharp peaks. Depending on the nature of the function, a continuous (CWT), discrete (DWT), or multi-resolution wavelet transform (MWT) can be applied.

In this paper, we use the DWT (Haar basis) to suppress spikes in an electric power system (EPS). Due to its ability to extract information in both time and frequency domain, DWT is considered a very powerful tool. The approach consists of decomposing the signal of interest into its detailed and smoothed components (high- and low-frequency). The detailed components of the signal at different levels of resolution localize the time and frequency of the event. Therefore, the DWT can extract the "short-time", "extreme value", and "high-frequency" features of EPS transient response spikes. DWT has been successfully applied to power systems for the analysis and detection of single event transients [14-15]. Following is a detailed discussion of theory and design methodology for the special-purpose filters for this application.

DWT-based filters can be used to localize abrupt changes in signals in time and frequency. The invariance to shift in time (or space) in these filters makes them unsuitable for pattern recognition problems. Therefore, creative techniques have been implemented to cure this problem [10-13]. These techniques range in their approach from calculating the wavelet transforms for all circular shifts and selecting the "best" one that minimizes a cost function [10], to using the entropy criterion [13] and adaptively decomposing a signal in a tree structure so as to minimize the entropy of the representation. In this paper a new approach to detection, classification, and cancellation of spikes has been proposed. The customized Haar wavelet basis created for this application are both translation- and scale-invariant and can represent a signal in a multi-scale format. While this is not the best fit for entropy criterion, it is well suited for the proposed detection, classification, and cancellation purposes [10-13].

From a viewpoint of functional analysis, we propose a new way to deal with the translation- and scale-invariant problem of discrete wavelet transform (DWT). Firstly, we adaptively renormalize the original signal. This procedure can be accomplished by using a signal-dependent filter whose impulse response is adaptively calculated by the first two moments of the original signal and a scale function of an orthonormal wavelet. Then, the re-normalized signal is decomposed using the conventional DWT. The final wavelet coefficients are proved to be both translation- and scale-invariant. The adaptive wavelet decomposition we propose represents a signal in a multi-scale format, and it may be not the "best" according to the entropy criterion, but it is very adaptive, therefore, it's more suited for recognition purpose. As an application, we apply our decomposition to the task of noise and spikes elimination for EPS. We define a new feature in the framework of our adaptive wavelet decomposition. This feature, consists of the relative energy values of the filters at each scale, is invariant with respect to shift, scaling and gray scale transforms, and, as experiments show, very effective for the task of scale-invariant denoising and discrimination [18].

Under normal operating conditions, ADAPT EPS exhibits colored background noise and spikes, impulse noise and spikes. In our experimental runs, we have collected data from various sensors over different lengths of time. It should be pointed out that the noise and spikes in EPS dataset may be modeled as nonstationary [19-21]. In this work, we assume that the changes in the noise and spikes PSD (power spectral density) are slow enough to allow a correct estimation of the prediction coefficients. The task of creating the filter banks for this study is based on translations and scaling of a set of basis functions (Harr basis in this case). An example of the generating function (mother wavelet) based on the Sinc function for the CWT is:

$$\psi(t) = 2Sinc(2t) - Sinc(t) = \frac{Sin(2\pi t) - Sin(\pi t)}{\pi t} \quad (1)$$

The subspaces of this function are generated by translation and scaling. For instance, the subspace of scale (dilation) *a* and translation (shift) *b* of the above function is:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (2)$$

When a function *x* is projected into this subspace, an integral would have to be evaluated to calculate the wavelet coefficients in that scale:

$$WT_{\psi}\{x\}(a,b) = \langle x, \psi_{a,b}\rangle = \int_R x(t)\overline{\psi_{a,b}(t)}dt \quad (3)$$

And therefore, the function *x* can be shown in term of its components:

$$x_a(t) = \int_R WT_{\psi}\{x\}(a,b).\psi_{a,b}(t)db. \quad (4)$$

Due to computational and time constraints it is impossible to analyze a function using all of its components. Therefore, usually a subset of the discrete coefficients is used to reconstruct the best approximation of the signal. This subset is generated from the discrete version of the generating function:

$$\psi_{m,n}(t) = a^{-m/2}\psi(a^{-m}t - nb). \quad (5)$$

Applying this subset to a function *x* with finite energy will result in DWT coefficints from which one can closely approximate (reconstruct) *x* using the coarse coefficients of this sequence:

$$x(t) = \sum_{m\in Z}\sum_{n\in Z}\langle x, \psi_{m,n}\rangle.\psi_{m,n}(t). \quad (6)$$

The MWT is obtained by picking a finite number of wavelet coefficients from a set of DWT coefficients. However, to avoid computational complexity, two generating functions are used to create the subspaces:

$$V_m \text{ Subspace: } \phi_{m,n}(t) = 2^{-m/2}\phi(2^{-m}t - n) \quad (7)$$

and

$$W_m \text{ Subspace: } \psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n). \quad (8)$$

From which the two (fast) wavelet transform pairs (MWT) can be generated:

$$\phi(t) = \sqrt{2}\sum_{n\in Z} h_n\phi(2t-n) \quad (9)$$

and

$$\psi(t) = \sqrt{2}\sum_{n\in Z} g_n\phi(2t-n) \quad (10)$$

In this paper the DWT has been used to suppress noise and reduce order of data in a wireless sensor network. Due to its ability to extract information in both time and frequency domain, DWT is considered a very powerful tool. The approach consists of decomposing the signal of interest into its detailed and smoothed components (high-and low-frequency). The detailed components of the signal at different levels of resolution localize the time and frequency of the event. Therefore, the DWT can extract the coarse features of the signal (compression) and filter out details at high frequency (noise). DWT has been successfully applied to system analysis for removal of noise and compression [22, 23]. In this paper we present how DWT can be applied to detect and filter out noise and compress signals. A detailed discussion of theory and design methodology for the special-purpose filters for this application follows.

The process to construct the proposed customized filters starts with discrete wavelets defined by wavelet and scaling functions introduced in equations (9) and (10) which are repeated here:

$$\phi(t) = \sqrt{2}\sum_{n\in Z} h_n\phi(2t-n) \quad (9)$$

and

$$\varphi(t) = \sqrt{2}\sum_{n\in Z} g_n\phi(2t-n) \quad (10)$$

The masks for these functions are obtained as:

$$\left\{\phi(0), \phi\left(\frac{1}{2^m}\right), \ldots\ldots, \phi\left(\frac{M-1}{2^m}\right)\right\} \quad (11)$$

and

$$\left\{0, 0, \ldots, 0, \varphi(0), \varphi\left(\frac{1}{\sigma}\right), \ldots\ldots, \varphi\left(\frac{N}{\sigma}\right)\right\} \quad (12)$$

As these two masks are convolved, the generating function (mother wavelet) mask can be obtained as:

$$F\left(\frac{k}{2^m}\right) \quad (-M \le k \le N) \quad (13)$$

Where for every integer k, integers $n_1^k, n_2^k, \ldots\ldots, n_q^k$ can be found to satisfy the inequality:

$$-3 < \mu - n_i^k + \frac{k\sigma}{2^m} < \frac{3\sigma}{2^m} \quad (1 \le i \le q) \quad (14)$$

The corresponding values from mother wavelet mask can then be taken to calculate: $\alpha_i^k = \frac{2^{m/2}}{\sigma}F\left(\frac{\rho_i^k}{2^m}\right)$, where

$$\rho_i^k = \left[(\mu - n_i^k)2^m + k\sigma\right] \quad (1 \le i \le q) \quad (15)$$

and

$$\frac{c_{-m,k}}{\sqrt{\alpha}} - \sum_{i=1}^{q} c_{ni}\alpha_i^k \quad (16)$$

Decomposing the re-normalized signal $\frac{c_{-m,k}}{\sqrt{\alpha}} \quad (k \in Z)$ according to the conventional wavelet transform, will result in the entire filter basis for different scales:

$$\frac{c_{-m+1,k}}{\sqrt{\alpha}}, \frac{d_{-m+1,k}}{\sqrt{\alpha}}, \frac{c_{-m+2,k}}{\sqrt{\alpha}}, \frac{d_{-m+2,k}}{\sqrt{\alpha}}, \ldots, \frac{c_{0,k}}{\sqrt{\alpha}}, \frac{d_{0,k}}{\sqrt{\alpha}} \quad (17)$$

These filter basis then can be applied to the diagnostic datasets of EPS and the coefficients of the reconstructed dataset (with spikes removed) can be extracted.

3. METHODOLOGY

As discussed in section 2 and as shown in figure 1, the proposed approach makes it possible to decompose a signal to its coarse and detailed components and adaptively filter out the undesired components. Scaling and translation properties of wavelet bank basis allows for a precise dissection of the signal in time and frequency domains.

Therefore, certain undesired time and/or frequency components of the signal can be separated accordingly.

Figure 1 shows the details of this transaction. Starting with the raw data from ADAPT S(t), the wavelet-based filters decompose the signal into the proper components U(t), depending on the basis, scale, and transition level chosen. The unwanted parts of the signal (in this case spikes) are removed to create the reconstructed signal U^(t). Then, the signal gets processed by diagnosis software which indicates the health status of components and sensors. The significance of the proposed method is that the reconstructed signal (after removal of spikes) has not been deteriorated by filters and still carries the information (and noise) it contained to begin with. Therefore, the noise as well as the original data can be used for further processing.

For diagnostic purposes, and specifically for detecting "stuck" components or sensors, removing noise may be harmful, because lack of noise indicates that a component/sensor is stuck. So, in general, it would make sense to distinguish these three cases:
(i) Removing spikes BUT NOT noise [of interest to diagnostic community]
(ii) Removing noise BUT NOT spikes
(iii) Removing noise AND spikes

A multiresolution analysis of the filter output suggests that noise can be preserved and spikes can be separated from the original signal by simply cancelling the proper layers in the output signal. Depending on the desired resolution in the output signal the detailed layers can also be dropped (keeping only coarser layers) so that the spike removal goal is achieved.

4. EXPERIMENTS

The proposed experimental setting consists of 3 main components as described below and illustrated in figures 1 and 2:

ADAPT EPS—A uniquely designed facility to enable the development, maturation, and benchmarking of diagnostic, prognostic, and decision technologies for system health management applications.

ProDiagnose—A software that processes all incoming environment data and acts as a gateway to a probabilistic inference engine. The inference engine analyzes the observations given to it by ProDiagnose, and computes diagnostic inferences. ProDiagnose uses the Arithmetic Circuit Evaluator, or ACE. ACE uses arithmetic circuits (ACs), which are compiled from Bayesian network models.

Haar Wavelet Filters—Algorithms serve to manipulate data produced by ADAPT so that they would be a good fit for ProDiagnose analysis. As has been the case in several experimental procedures on ADAPT, unwanted transient response, high order of data to be computed, and noise have adverse effects on computations and have the potential to throw off the diagnostic and prognostic analysis.

The DSP algorithms (Haar wavelet filters) serve to enhance data produced by ADAPT so that they would be a good fit for diagnostic analysis. As has been the case in several experimental procedures on ADAPT, spikes have the potential to throw off the diagnostic analysis. In this set of algorithms designed for ADAPT EPS, a wavelet based approach has been considered to suppress the effect of anomalies on datasets. As shown in figures 3 and 4, the proposed wavelet-based filters decompose the dataset into its detailed and coarse components.

Figures 3 and 4 show two datasets from sensors in ADAPT that have undergone filtering by the proposed wavelet-based filters. The figures show the original signal (in red) vs. the reconstructed version (in yellow) with spikes and/or noise removed. Of course, the ideal signal for ADAPT EPS diagnostic purposes is the one with spikes (only) removed and is highlighted in green background. Additionally, we have tried this technique on a signal that is nominally non-flat. Figure 5 verifies that in the absence of spikes the signal is unaffected and the process works equally well.

5. CONCLUSIONS

Using discrete Haar wavelets, we have successfully removed spikes without removing noise and damaging data in diagnostic signals. The technique shows promise on ADAPT EPS data. This effort has resulted in a set of Haar wavelet filters that are shift invariant and can adaptively adjust so that the desired components of a signal (noise) are preserved while the unwanted components (spikes) are removed. The experiments show that the proposed technique is also capable of removing both noise and spikes as well as removing noise and preserving spikes (see figures 3 and 4). By setting thresholds for the wavelet basis (as discussed in section 2 of this paper) one can even filter out certain components of the noise as though a high-pass, band-pass, or low-pass filter were applied to the dataset.

Another important aspect of the proposed technique is its low cost computational requirements and high speed results. These filters can now be implemented in hardware where speeds in the order of nano-seconds can be obtained. Together with low power consumption, this creates the perfect environment for diagnostics platforms in most EPSs (i.e. spacecrafts, aircrafts, powerstations, etc.) where real-time decision making is of great importance.

Compared to standard methods or standard wavelet filters, the proposed techniques offers more improved resolution, accuracy, and efficiency. As is evidet from figures 3, 4, and 5, the approach is well suited for removing anomalies from dataset. At the same time, the filters are adaptive in terms of time and frequency so to match the proper unwanted signals (nois, spike, or both) at the right instant. Threshold adjustment is anothe rfeature that allows for filtering each anomaly by the right amount. This feature helps differentiate between unwanted spikes and the desired transient response.

In future work we hope to investigate how this technique can be used as a filtering step before performing diagnosis using probabilistic methods, for example by means of Bayesian networks or arithmetic circuits. The data obtained from filtered datasets will be used in diagnostics algorithms and compared to non-filtered data to measure any improvements and assess the proposed filtering technique. Additionally, the multiresolution and multiorientation properties of the proposed filters will be used to reduce the order of datasets and improve the speed of the diagnostic algorithms.

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BIOGRAPHY

Ehsan Sheybani *is an Associate Professor in Computer Engineering at Virginia State University. He obtained his Ph.D., MS, and BS in Electrical Engineering from University of South Florida, Florida State University, and University of Florida, respectively. Dr. Sheybani has published many journal articles and conference papers (IEEE, ACM, ASEE, SPIE). His professional activities include serving as a PI/Co-PI for NSF, NIH, NASA, DoD, and DEd grant proposals, reviewer for several IEEE transactions, track-chair of IEEE/ACM WTS 2006-2009 symposia, and reviewer for NIH and DoD. His teaching and research areas are Digital Signal Processing and Wireless Sensor Networks.*

Ole J. Mengshoel *holds a Ph.D. degree in computer science from the University of Illinois, Urbana-Champaign. His undergraduate degree, also in computer science, is from the Norwegian Institute of Technology, Norway (now NTNU). He is currently a Senior Systems Scientist with Carnegie Mellon Silicon Valley. He is also affiliated with the NASA Ames Research Center, Moffett Field, CA. Prior to joining Carnegie Mellon Silicon Valley, he was a Senior Scientist and Research Area Lead at USRA/RIACS, a Research Scientist in the Decision Sciences Group at Rockwell Scientific, and a Research Scientist in the Knowledge-Based Systems at SINTEF, Norway. At NASA, he has a leadership role in the Diagnostics and Prognostics Group in the Intelligent Systems Division, where his current research focuses on reasoning, machine learning, diagnosis, prognosis, and decision support under uncertainty - often using probabilistic graphical models and in particular Bayesian networks – with aerospace applications of interest to NASA. Dr. Mengshoel is a member of AAAI, ACM, and IEEE, and has numerous times served as a Reviewer and on Program Committees. He has published over 35 articles and papers in journals, conferences, and workshops, and holds four U.S. patents.*

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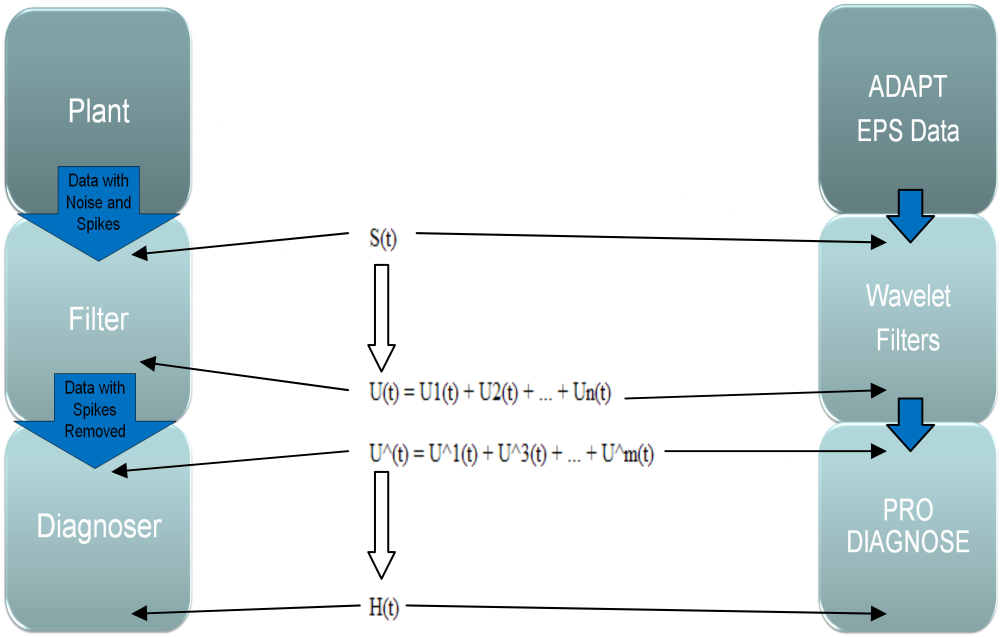

Figure 1 – General and specific functional block diagram of the proposed diagnostic system.

Figure 2 -- The ADAPT EPS at NASA Ames Research Center. (Courtesy of NASA Ames)

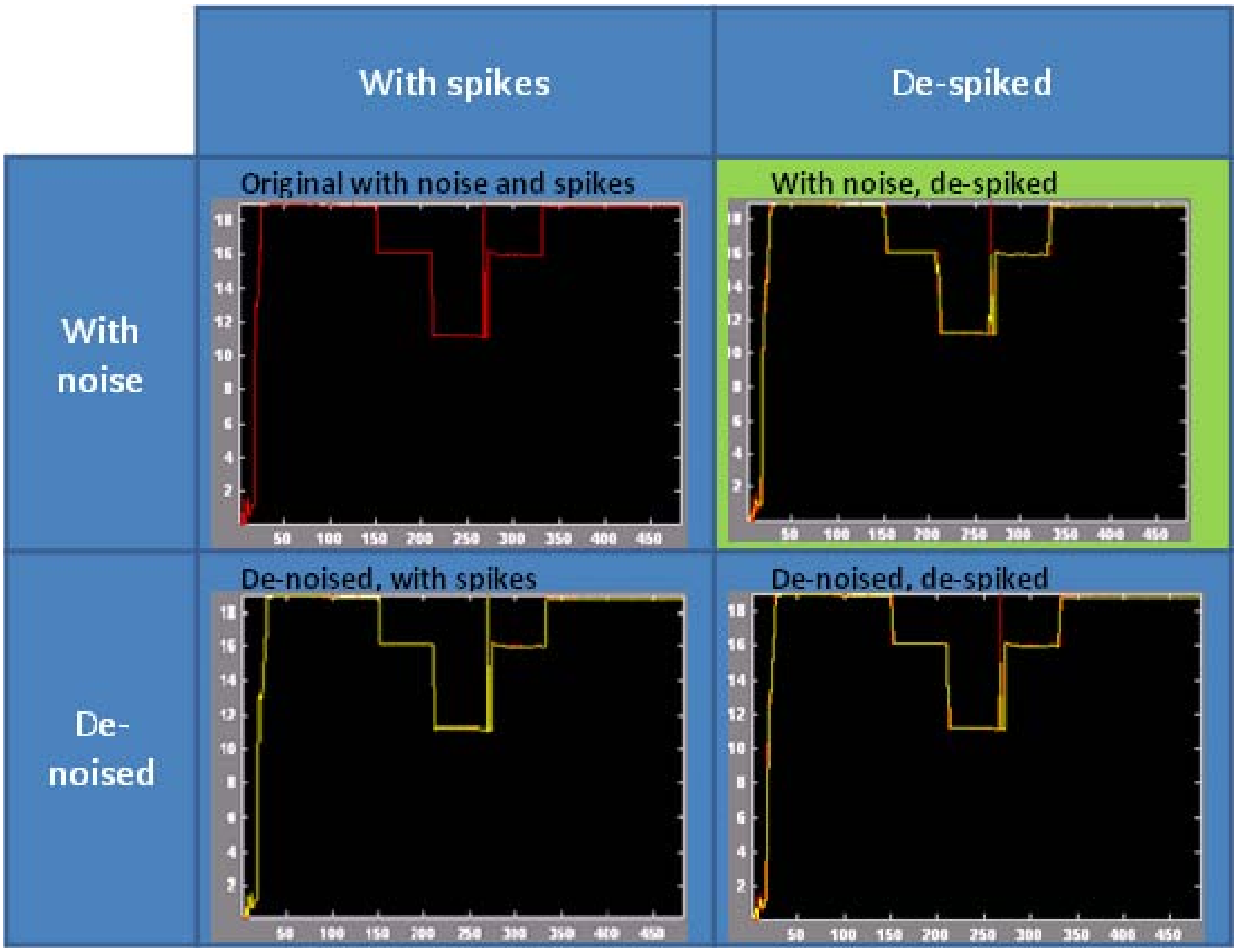

Figure 3 -- Enhancements made to ADAPT 957-IT140 dataset to cancel noise and spikes in the dataset. For the purposes of EPS diagnostics, only the set with noise and no spike is desirable (Green background).

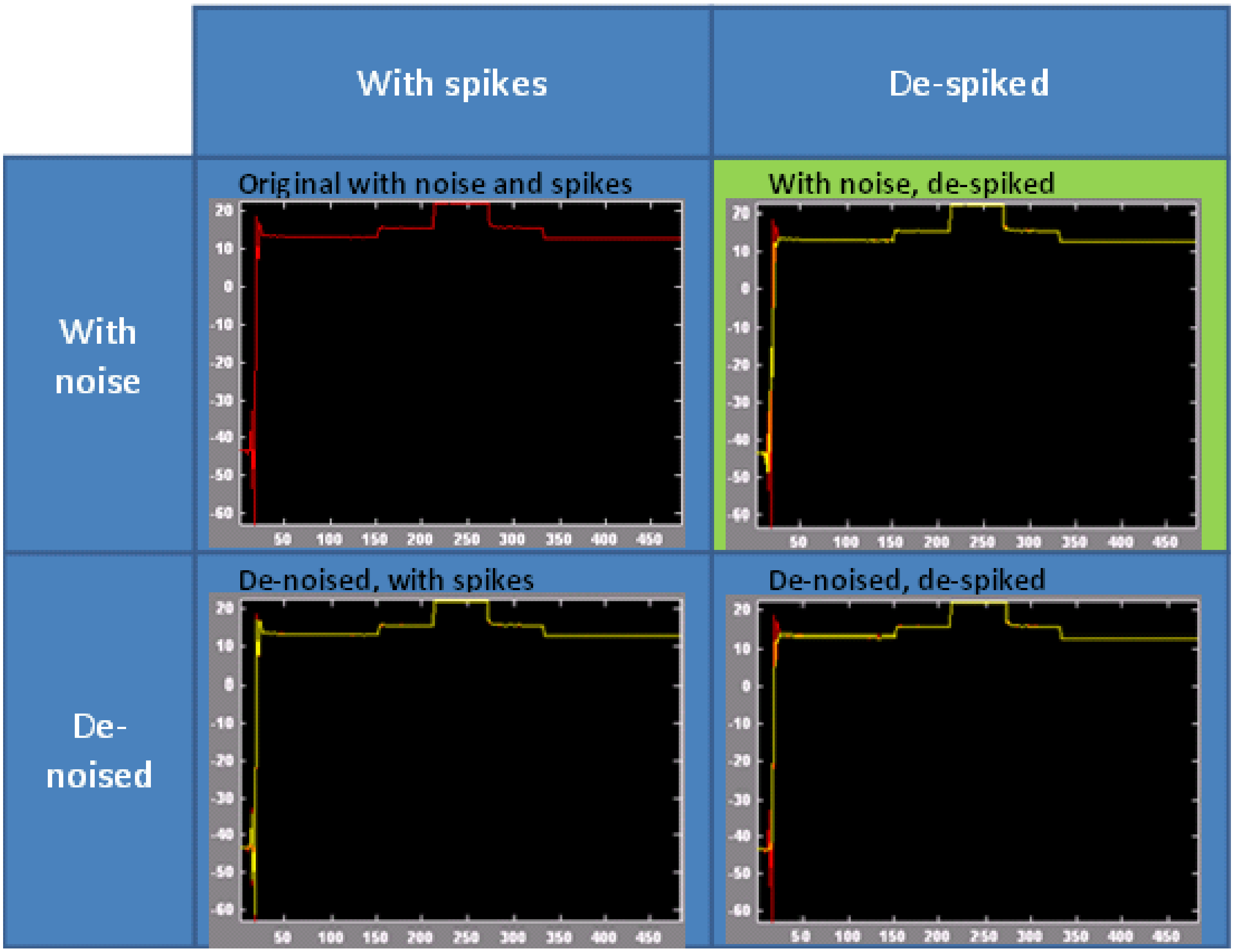

Figure 4 -- Enhancements made to ADAPT 957-XT167 dataset to cancel noise and spikes in the dataset. For the purposes of EPS diagnostics, only the set with noise and no spike is desirable (Green background).

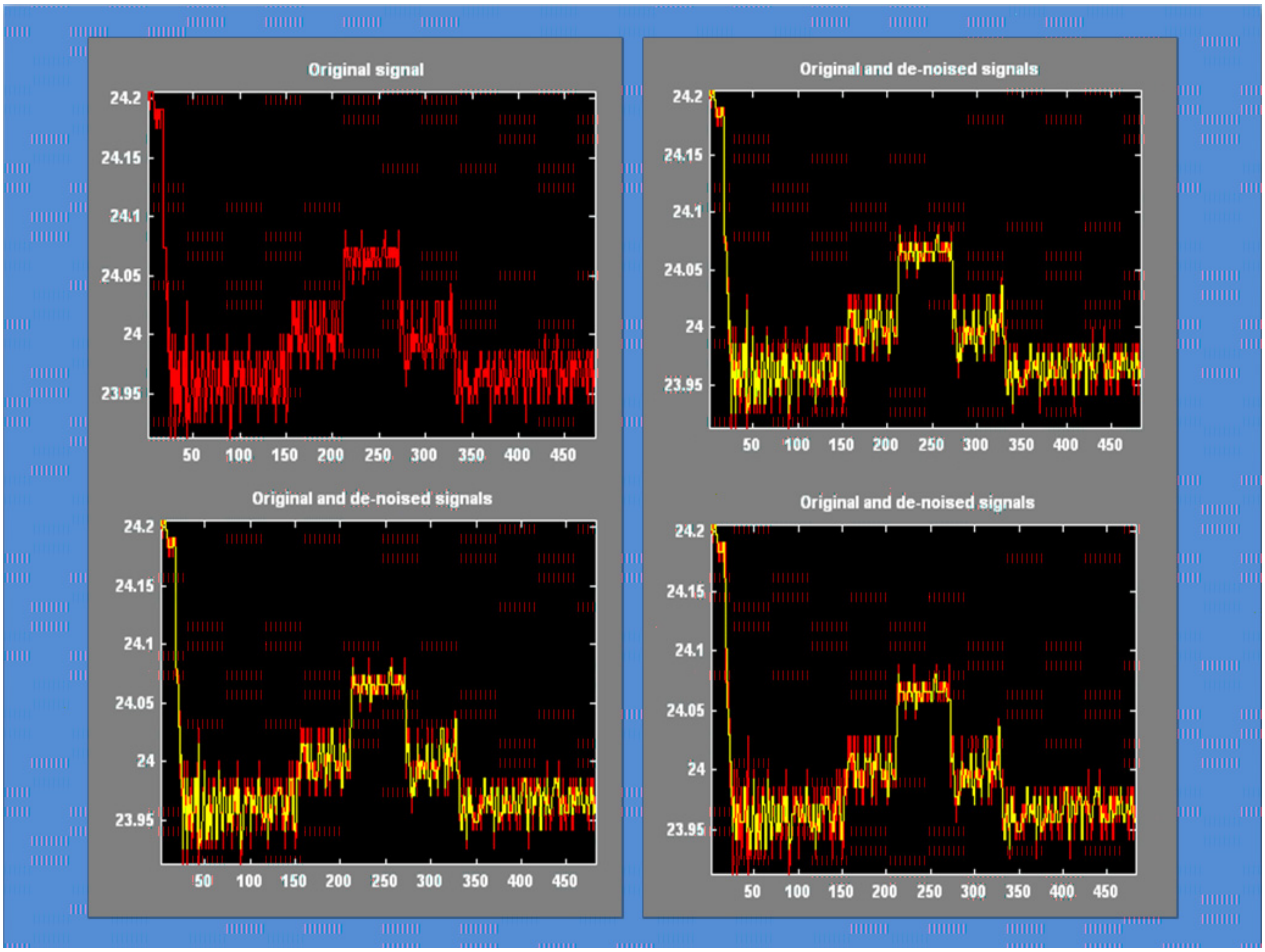

Figure 5 -- Enhancements made to ADAPT 957-E240 dataset to cancel noise and spikes in the dataset. Original signal (top left - red) and de-noised signal (yellow) at three different levels and thresholds have been shown. As can be seen, the transient response has been preserved whether the noise is cancelled or not.