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A Bayesian sequential processor approach to spectroscopic portal system decisions

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ABSTRACT

The development of faster more reliable techniques to detect radioactive contraband in a portal type scenario is an extremely important problem especially in this era of constant terrorist threats. Towards this goal the development of a model-based, Bayesian sequential data processor for the detection problem is discussed. In the sequential processor each datum (detector energy deposit and pulse arrival time) is used to update the posterior probability distribution over the space of model parameters. The nature of the sequential processor approach is that a detection is produced as soon as it is statistically justified by the data rather than waiting for a fixed counting interval before any analysis is performed. In this paper the Bayesian model-based approach, physics and signal processing models and decision functions are discussed along with the first results of our research.

1. INTRODUCTION

The need to investigate new techniques and technologies that can provide for more sensitive detection of terrorist threats around the world demand that meaningful approaches be developed to solving many critical security problems for protection of valuable resources and people. With the advent of high power computing, one such methodology that has evolved from pure theory and speculation is the probabilistic approach using Bayesian methods. Here particular problems are cast into a Bayesian framework based on the well-known Bayes theorem of statistics and solved using Monte Carlo simulation methods. One of the major challenges is to develop techniques that can be applied to time/space dependent problems (e.g. cargo container monitoring in radiation detection—a nonstationary problem) and provide a timely solution. This paper addresses the first step in investigating the problem of enhancing radioactive contraband signals from noisy radiation measurements using a Bayesian approach.

Radionuclide detection is a critical first line defense to detect the transportation of radiological materials by potential terrorists. Detection of these materials is particularly difficult due to the inherent low-count emissions produced. These low-count emissions result when sources are shielded to disguise their existence or, when being transported, are in relative motion with respect to the sensors. Active interrogation with a low intensity neutron source, as required by safety considerations, also produces low-count emissions. The basic problem we propose is to detect, classify and estimate contraband from highly uncertain (noisy) low-count, radionuclide measurements using a statistical approach based on Bayesian inference and physics-based signal processing.

The identification of radionuclide sources from their gamma ray emission signatures is a well-established discipline using spectroscopic techniques and algorithms.[1−3] Numerous tools exist to aid the analyst interpreting these signatures. Historically, sufficient time existed to accumulate the data necessary to reasonably identify these sources. Furthermore, highly accurate detectors exist that yield an accurate spectrum. Unfortunately, these techniques fail on low-count measurement data. Contemporary tools reveal that the underlying algorithms rely upon heuristic approaches based upon the experience of analyst. Most of these tools may even require the intervention of a trained practitioner to analyze the results and guide the interpretation process. In a terrorist type scenario, this is not acceptable, since timely and accurate performance is imperative.

Automatic radionuclide identification from low-count gamma ray emissions is a critical capability that is very difficult to achieve. In an operational setting this becomes a particularly challenging problem because the available data consists of low energy count, impulsive-like, time series measurements (energy vs time) in the form of an event mode sequence (*EMS*). Moreover, the algorithm must cope with background noise, finite detector resolution, and the heterogeneous media along the propagation paths between the sources and detectors. Detection/classification/estimation, therefore, becomes a question of gaining signal-to-noise ratio (*SNR*) in this case, since low-count emissions become buried in the background and Compton scattering noise, rendering a meaningful detection highly improbable. However, with the advent of high speed, high throughput computers,

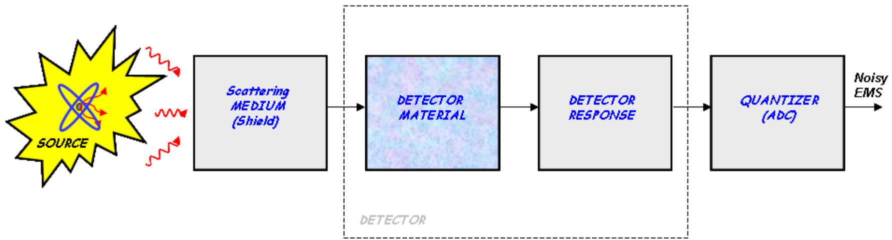

Figure 1. Gamma-ray evolution and measurement: Radionuclide source (*EMS*), medium transport (physics), detector material interaction, detector temporal response (pre-amplification/pulse shaping) and A/D conversion with quantization noise.

physics-based statistical models that capture the essence of the radionuclide detection/classification/estimation problems can now be incorporated into a Bayesian sequential processor capable of on-line, near real-time operation.

Radiation detection, that is, the unique characterization of an unstable radionuclide based on its electromagnetic emissions has been an intense area of research and development for well over 50 years.[4−5]) It is well-known that a particular radionuclide can be uniquely characterized by two basic properties: its *energy* emitted in the form of photons or gamma-rays (γ-rays) and its radioactive *decay rate*. Knowledge of one or both of these parameters is a unique representation of a radionuclide. Mathematically, we define the pair, $[\{\epsilon_i\}, \{\lambda_i\}]$, as the respective energy level (MeV) and decay rate (probability of disintegration/nuclei/sec) of the i^{th}-component of the elemental radionuclide. Although either of these parameters can be used to uniquely characterize a radionuclide, only one is actually necessary—unless there is uncertainty in extracting the parameter. Gamma ray spectrometry is a methodology utilized to estimate the energy (probability) distribution or spectrum by creating a histogram of measured arrival data at various levels (count vs. binned energy).[5] It essentially decomposes the test sample γ-ray emissions into energy bins discarding the temporal information. The sharp lines are used to identify the corresponding energy bin detecting the presence of a particular component of the radionuclide. In the ideal case, the spectrum consists only of lines or spikes located at the correct bins of each constituent energy, ϵ_i, uniquely characterizing the test radionuclide sample. A search of the spectrum for the strong presence of these lines is used for identification.

Our approach is different in that it models the source radionuclides by decomposing them uniquely as a superposition (union) of monoenergetic sources that are then smeared and distorted as they propagate through the usual path to the output of the detector for measurement and counting. The problems of interest are then defined in terms of this unique, orthogonal representation in which solutions based on extracting this characterization from uncertain detector measurements can be postulated. Using the recently developed particle filters (*PF*) suggested by others,[6−?] and embedding the physics-based models, will lead to the formulation of critical problems such as detection, classification and estimation of threat radionuclides. Using a sequential Bayesian framework enables us to develop a near real-time approach to solving this suite of problems that are based on the unique monoenergetic decomposition model.

This approach becomes more important especially when only low-count data is available or equivalently a rapid detection is required. In general, the model-based approach to signal processing incorporates information about the process (γ-ray transport), measurement system (semiconductor detectors) and uncertainty or noise (background, random noise, amplitude fluctuations, time jitter, etc.) in the form of mathematical models to develop a model-based processor (*MBP*) capable of enhancing or equivalently extracting signals from highly uncertain environments[5] for the radiation detection problem (see Fig. 1). Very little work has been performed applying the Bayesian approach to this specific application primarily because of its difficulty and inability to characterize the physics adequately; however, *none* has been performed based on the *EMS* representation of γ-ray transport. We discuss the development of a physics-based deconvolution processor in Sec. 4—the first step in improving the γ-ray spectral enhancements as well estimating the unknown radionuclide. In Sec. 5 we discuss the results for both simulated and measured experimental data. We summarize our results in the final section.

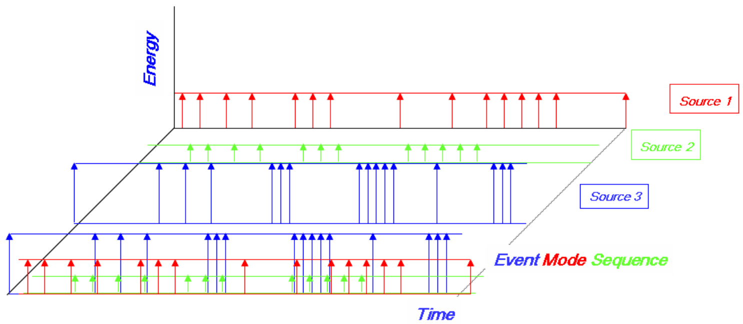

Figure 2. Monoenergetic Source Decomposition: Individual constituent *EMS* and ideal composite *EMS*.

2. EVENT MODE SEQUENCE

In this section we develop a detailed representation of the event mode sequence in terms of its monoenergetic decomposition. From this decomposition, we then develop the basic signal processing model in terms of the random processes that govern its evolution. γ-ray interactions are subject to the usual physical interaction constraints of scattering and attenuation as well as uncertainties intrinsic to the detection process. Energy detectors are designed to estimate the γ-ray energy from the measured (charge) voltage. A typical detector is plagued with a variety of extraneous measurement uncertainty that creates inaccuracy and spreading of the measured impulse (and therefore γ-ray energy). The evolution of a γ-ray as it travels through the medium and interacts with materials, shield and the detector is shown in Fig. 1. It is important to realize that in the diagram, the source radionuclide is represented by its constituents in terms of monoenergetic (single energy level) components and arrival times as $\xi(\epsilon_i, \tau_i)$. Since this representation of the source radionuclide contains the constituent energy levels and timing, then all of the information is completely captured by the sets, $[\{\epsilon_i\}, \{\tau_i\}]\,,\ i = 1, \cdots, N_\epsilon$. The arrivals can be used to extract the corresponding set of decay constants, $\{\lambda_i\}$ which are related. Thus, from the detector measurement of *EMS* arrivals, a particular radionuclide can be uniquely characterized. The constituent energy levels (spikes), $\{\epsilon_i\}$ and arrival times, $\{\tau_i\}$, extracted from the *EMS* are depicted in Fig. 2 where we show the union (superposition) of each of the individual constituent monoenergetic sequences composing the complete radionuclide *EMS*. Note that there is no overlapping of arrivals–a highly improbable event.

So we see that the signal processing model developed from the propagation of the γ-ray as it travels to the detector is measured and evolves as a distorted *EMS*. Next, we develop a representation of the event mode sequence in terms of its monoenergetic decomposition. Define $\xi(t; \epsilon_i, \tau_i, \lambda_i)$ as the component *EMS* sequence of the i^{th}-monoenergetic source at time t of *energy level* (amplitude), ϵ_i and *arrival time*, τ_i with *decay rate*, λ_i —as a single impulse, that is, $\xi(t; \epsilon_i, \tau_i, \lambda_i) = \epsilon_i \delta(t - \tau_i)$ and rate λ_i. Thus, we note that the ideal *EMS* is composed of sets of energy-time pairs, $\{\epsilon_i, \tau_i\}$. In order to define the entire emission sequence over a specified time interval, $[t_o, T)$, we introduce the set notation, $\underline{\tau}_i := \{\ \tau_i(1)\ \cdots\ \tau_i(N_\epsilon(i))\ \}$ at the n^{th}-arrival with $N_\epsilon(i)$ the total number of *counts* for the i^{th}-source in the interval. Therefore, $\xi(t; \epsilon_i, \underline{\tau}_i, \lambda_i)$ results in a unequally-spaced impulse train given by (see Fig. 2)

$$\xi(t; \epsilon_i, \underline{\tau}_i, \lambda_i) = \sum_{n=1}^{N_\epsilon(i)} \xi(t; \epsilon_i, \tau_i(n), \lambda_i) = \sum_{n=1}^{N_\epsilon(i)} \epsilon_i \delta(t - \tau_i(n)) \tag{1}$$

The *interarrival* time, is defined by $\triangle\tau_i(n) = \tau_i(n) - \tau_i(n-1)$ for $\triangle\tau_i(0) = t_o$ with the corresponding set definition (above) of $\underline{\triangle}\tau_i$ for $i = 1, \cdots, N_\epsilon(i) - 1$.

Extending the *EMS* model from a single source representation to incorporate a set of N_ϵ-monoenergetic sources. Suppose we have a radionuclide source whose *EMS* is decomposed into its N_ϵ-monoenergetic source components, $\xi(t; \epsilon, \tau, \lambda)$. From the composition of the *EMS* we know that

$$\xi(t; \epsilon, \tau, \lambda) = \sum_{i=1}^{N_\epsilon} \sum_{n=1}^{N_\epsilon(i)} \xi(t; \epsilon_i, \tau_i(n), \lambda_i) = \sum_{i=1}^{N_\epsilon} \sum_{n=1}^{N_\epsilon(i)} \epsilon_i \delta(t - \tau_i(n)) \tag{2}$$

Clearly, since the *EMS* is the superposition of Poisson processes, then it is also a composite Poisson process[9] with parameters: $\lambda = \sum_{i=1}^{N_\epsilon} \lambda_i, \quad \epsilon = \sum_{i=1}^{N_\epsilon} \epsilon_i, \quad N_\xi = \sum_{i=1}^{N_\epsilon} N_\epsilon(i)$ for λ the total decay rate, ϵ the associated energy levels and N_ξ the total counts in the interval, $[t_o, T)$. Note that the composite decay rate is the superposition of *all* of the individual component rates. This follows directly from the fact that the sum of exponentially (Poisson) distributed variables are exponential (Poisson). We note that the (composite) *EMS* of the radionuclide directly contains information about λ, but not about its individual components—unless we can extract the monoenergetic representation (Eq. 2) from the measured data.

Statistically, the *EMS* can be characterized by the following properties:

- non-uniform arrival time samples, $\tau_i(n)$
- monoenergetic source components, $\xi(t; \epsilon_i, \tau_i(n), \lambda_i)$ having their own unique decay rate, λ_i
- unique energy level, ϵ_i
- gamma distributed arrival times, $\tau_i(n) \sim \Gamma(k, \tau_i)$
- Poisson distributed counts, $N_\epsilon(i) \sim \mathcal{P}(N_\epsilon(n) = m)$
- exponentially distributed interarrival times, $\triangle\tau_i(n) \sim \mathcal{E}(\lambda_i \triangle\tau_i(n))$.
- composite decay rate, λ

Next we consider the measurement of the *EMS* along with its inherent uncertainties.

3. GAMMA-RAY DETECTOR MEASUREMENTS

In this section we develop a physics-based γ-ray detector model illustrating the task of characterizing the physics in terms of statistical signal processing models. Using the mathematical description of the *EMS* in terms of its monoenergetic source decomposition model discussed previously, we show how this ideal representation must be modified because of the distortion and smearing effects that occur as the γ-rays propagate according to the transport physics of the radiation process.

Using the mathematical description of the *EMS* in terms of its monoenergetic source decomposition model discussed previously, we show how this ideal representation must be modified because of the distortion and smearing effects that occur as the γ-rays propagate according to the transport physics of the radiation process. Typically, these are quantified in terms of γ-ray spectral properties of energy "peak width" and "peak amplitude". The uncertainties evolve from three factors inherent in the material and instrumentation: inherent statistical spread in the number of charge carriers, variations in the charge collection efficiency and electronic noise.[5] In general, the energy resolution is defined in terms of a Gaussian random variable, $\epsilon_i \sim \mathcal{N}\left(\bar{\epsilon}_i, \sigma^2_{\epsilon_i}\right)$.

Next we consider uncertainties created in the associated pulse processing system that consists of a pre-amplifier and pulse shaping circuits. Here we concentrate on the amplitude output of the pulse shaper, since it carries not only the quantified γ-ray energy information, but also it is used for the detector timing circuits (gating pulses, logic pulses, etc.). The shaped pulse is converted to a logic pulse in order to extract precise timing information (arrival times, interarrival times, etc.). We consider the pulse shaper circuitry capable of taking the "raw" material pulse amplifying and shaping it to create a Gaussian pulse shape.[5] Once the Gaussian pulse amplitude, which is proportional to the original γ-ray energy, is digitized or quantized by the analog-to-digital converter (*ADC*), the critical *EMS* parameters, $[\{\epsilon_i\}, \{\tau_i\}, \{\lambda_i\}]$, energy level, arrival time and decay rate can be extracted for further analysis and processing. From this data all other information can be inferred about the identity and quantity of the test radionuclide.

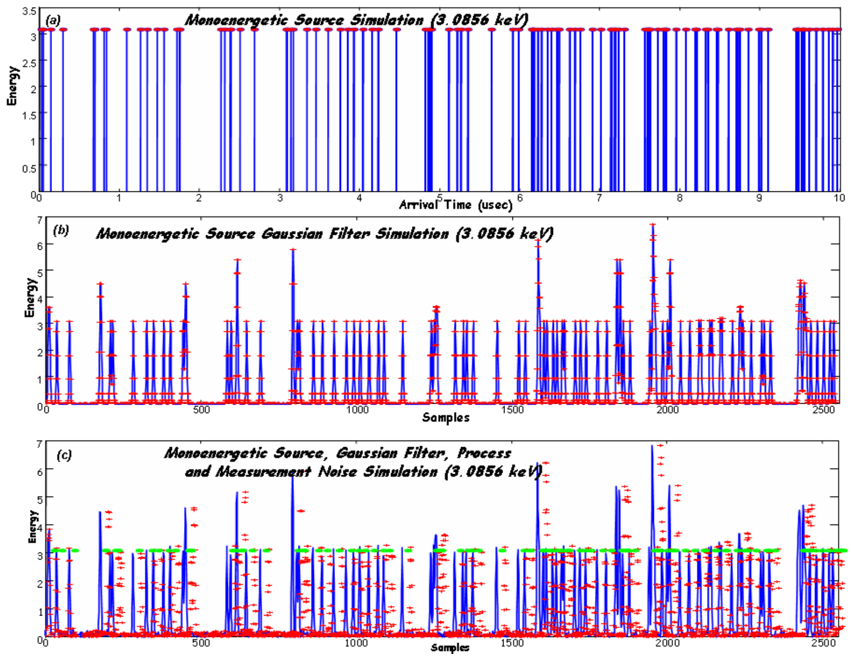

Figure 3. Monoenergetic Source Simulation: (a) True Source EMS (3.086 keV). (b) Gaussian Filtered EMS. (c) Gaussian Filtered with additive Process ($R_{ww} = 10^{-6}$) and Measurement ($R_{vv} = 10^{-2}$) noises.

3.1 Physics Model Simulation

Before we close this section, let us consider the development of a "basic" physics simulator that will enable us to generate the *EMS* for processing. Here the idea is to essentially generate an *EMS* that provides the source input to the pulse shaping circuit, that is, to transport the γ-rays emitted by the radionuclide source through the medium (shield) to the detector where the γ-ray energies are converted to electrons producing the charge. The corresponding output voltage of this process is then amplified and shaped by the pulse shaping circuits for input to the quantizer as depicted in Fig. 1.

The simple radiation transport synthesizer was developed by Meyer and others[10] for signal analysis purposes. It consists of specifying the radionuclide in terms of its *EMS* and corresponding monoenergetic source decomposition then transporting this sequence through the medium (shield) along with its inherent scattering to the detector. At the detector the "surviving" or escaping γ-ray photons are transported through the detector material (semiconductor) again being absorbed and scattered with the final surviving photons providing the current pulse input to the shaping circuitry as shown in Fig. 1. After initializing the radionuclide and its corresponding monoenergetic source decomposition, the simulator transports the "ideal" *EMS* through the shield that incorporates both absorption (attenuation) and scattering (Compton) properties using the prescribed shield parameters. The output of this step is specified by the percentage of the photons escaping the shield and those captured or absorbed by the material and converted to thermal energy. The surviving photons escaping are then transported to the detector material where they undergo further absorption and scattering with the survivors converted to charge (electrons) provided as the input to the detector shaping circuitry. We show a typical ideal EMS output of the synthesizer in Fig 3a and the corresponding pulse shaping circuit output in *(b)* along with a noisy output in *(c)* represent the input to the quantizer.

Next we define a *signal processing model* that captures the major characteristics of the detector in order to formulate our model-based approach to the radiation detection problem. Consider the diagram again of the overall detector system shown in Fig. 1. Here we see how the *EMS* is transported through the medium (scattering and attenuation) to the detector and each photon is deposited in the detector material, charge is collected and a voltage created which passes onto pulse shaping electronics that are contaminated with random measurement noise followed by the quantization to produce the noisy output measurement. Thus, from the i^{th}-monoenergetic component we have

$$p_{m_i}(t) = \sum_{n=1}^{N_\epsilon(i)} \xi(t; \epsilon_i, \tau_i(n), \lambda_i) \star r(t) + w_{\tau_i}(t) = \sum_{n=1}^{N_\epsilon(i)} \epsilon_i r(t - \tau_i(n)) + w_{\tau_i}(t) \tag{3}$$

where $r(t)$ is a rectangular window of unit amplitude defined within $\tau_i(n) \leq t \leq \tau_i(n-1)$. The uncertain (random) amplitude is Gaussian, $\epsilon \sim \mathcal{N}(\overline{\epsilon}_i, \sigma^2_{\epsilon_i})$, with inherent uncertainty representing the material charge collection process time "jitter" by the additive zero-mean, Gaussian noise, $w_{\tau_i} \sim \mathcal{N}(\overline{\tau}_i, \sigma^2_{w_{\tau_i}})$ and $\underline{\tau}(n) \rightarrow \tau_i(n); n = 1, \cdots, N_\epsilon(i)$. Therefore, the material output pulse train for the i^{th}-source is given by $s(t) = H_S(t) \star p_{m_i}(t) + v(t)$. Extending the model to incorporate all of the N_ϵ-sources composing the radionuclide leads to the superposition of all of the monoenergetic pulse trains, that is, $p_m(t) = \sum_{i=1}^{N_\epsilon} p_{m_i}(t)$. The uncertain material pulse, $p_m(t)$, is then provided as input to the pulse shaping circuitry. Here the preamplifier and pulse shaper are characterized by a Gaussian filter with impulse response, $H_S(t)$ with output given by

$$s(t) = H_S(t) \star p_m(t) + v(t) \tag{4}$$

where the uncertainty created by instrumentation noise is modeled through the additive zero-mean, Gaussian noise source, $v \sim \mathcal{N}(0, \sigma_v^2)$. The shaped pulse is then quantized ($t_k \rightarrow t$) and digitally processed to extract the energy levels and timing information for further processing. Due to quantization limitations the *ADC* inherently contaminates the measured pulse with zero-mean, Gaussian quantization noise, $v_q(t_k)$ while there exists background radiation noise, $b(t_k)$ that must also be taken into account. At this point, we could also develop a signal processing model of the background, but we choose simplicity. We just simply model it as an additive disturbance at the output of the quantizer given by $b(t_k)$ giving us the final expression at the output of the quantizer as

$$z(t_k) = s(t_k) + b(t_k) + v_q(t_k) \tag{5}$$

with $v_q \sim \mathcal{N}(0, \sigma_q^2)$.

So we see that the entire *EMS* can be captured in a signal processing model with the key being the monoenergetic source decomposition representation of radiation transport. Next we start with this model and convert it to state-space Markovian form directly for Bayesian processing. In our problem, the *EMS* is the noisy input sequence characterized by both input and noise processes, that is, ξ and $w_\tau \rightarrow w$. The states are part of the preamplifier and Gaussian pulse shaping system and the output is the quantized measurement, that is, $z(t_k) \rightarrow y(t)$. To be more specific, we use $\xi(t; \epsilon_i, \tau_i, \lambda_i)$, the i^{th}-monoenergetic source including both amplitude and timing uncertainties as a Poisson input to our Markovian model above along with the matrices, A, B, C, specifying the pulse shaping circuit parameters transformed to state-space form, $H_S \rightarrow Markovian$.

To see this consider the state-space representation for a *single* monoenergetic source is given by the following set of relations:

$$\begin{array}{rcll}
\dot{x}_i(t) & = & A_i x_i(t) + \mathbf{b}_i \xi\,(t; \epsilon_i, \underline{\tau}_i, \lambda_i) + \mathbf{w}_i w_{\tau_i}(t) & \text{[Source]} \\
y(t) & = & \mathbf{c}_i' x_i(t) + v(t) & \text{[Pulse Shaper]} \\
z(t_k) & = & y(t_k) + v_q(t_k); \quad i = 1, \cdots, N_\epsilon & \text{[ADC]}
\end{array} \tag{6}$$

Expanding this model over i to incorporate the N_ϵ-monoenergetic source components gives the extended state vector, $x(t) = [x_i(t) \mid x_2(t) \mid \cdots \mid x_{N_\epsilon}(t)\,]'$ where each component state is dimensioned N_x and therefore, $x \in \mathcal{R}^{N_x N_\epsilon \times 1}$. Thus, the overall *radiation detection* state-space model for N_ϵ monoenergetic sources is given by: $A = \text{diag}[A_i]$, $B = \text{diag}[B_i]$, $C = \left[\, \mathbf{c}_1' \mid \mathbf{c}_2' \mid \cdots \mid \mathbf{c}_{N_\epsilon}' \right]$.

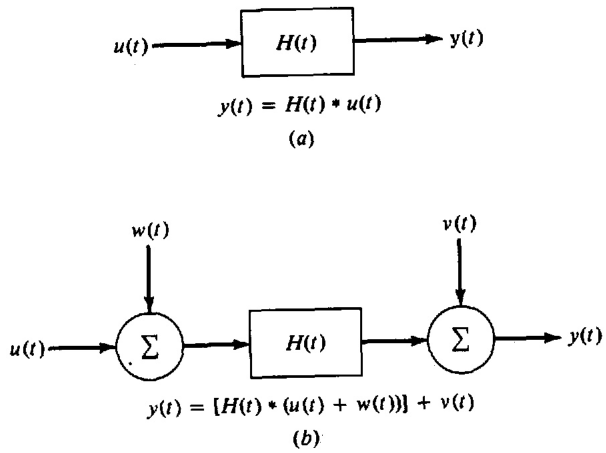

Figure 4. Model-Based Deconvolution Problem: (a) Deterministic problem. (b) Stochastic problem (Gauss-Markov formulation).

It is interesting to note some of the major properties of this model. The first feature to note is that the *monoenergetic decomposition* of the radionuclide source is *incorporated* directly into the model structure. For instance, it we are searching for a particular radionuclide and we know its major energy lines that uniquely describe its spectrum, we can choose the appropriate value of N_ϵ and specify its corresponding mean energy levels and decay rates directly—this is the physics-based approach. We also note that the corresponding noise and statistics are easily captured by this structure as well. This formulation is a continuous-discrete or simply "sampled-data" model, since the *ADC* in used in the detection scheme. So we see that the entire *EMS* can be captured in a signal processing model with the key being the monoenergetic source decomposition representation of radiation transport.

4. PHYSICS-BASED BAYESIAN DECONVOLUTION PROCESSOR

In this section we consider extending the *MBP* algorithm to solve the problem of estimating an unknown input from data that have been "filtered." This problem is called *deconvolution* in signal processing literature and occurs commonly in seismic and speech processing[11] as well as transient problems,[12]13.

In many measurement systems it is necessary to deconvolve or estimate the input to an instrument given that the data are noisy. The basic deconvolution problem is depicted in Fig. 4*a* for deterministic inputs $\{u(t)\}$ and outputs $\{y(t)\}$. The problem can be simply stated as follows: **GIVEN** the impulse response, $H(t)$ of a linear system and outputs $\{y(t)\}$, **FIND** the unknown input $\{u(t)\}$ over some time interval.

In practice this problem is complicated by the fact that the data are noisy and impulse response models are uncertain. Therefore, a more pragmatic view of the problem would account for these uncertainties. The uncertainties lead us to define the *stochastic deconvolution problem* shown in Fig. 4*b*. This problem can be stated as follows: **GIVEN** a model of the linear system, $H(t)$ and discrete noisy measurements $\{y(t)\}$, **FIND** the minimum (error) variance estimate of the input sequence $\{u(t)\}$ over some time interval.

The solution to this problem using the Bayesian *MBP* algorithm involves developing a model for the input and augmenting the state vector.[12] Suppose we utilize a discrete Gauss-Markov model and augment the following Gauss-Markov model of the input signal:

$$u(t) = F(t-1)u(t-1) + n(t-1) \tag{7}$$

where $n \sim \mathcal{N}(0, R_{nn}(t))$. The augmented Gauss-Markov model is given by $X_u := [x' \mid u']'$ and $w_u' := [w \mid n]$:

$$X_u(t) = A_u(t-1)X_u(t-1) + w_u(t-1)$$

and

$$y(t) = C_u(t)X_u(t) + v(t)$$

The matrices in the augmented model are given by

$$A_u(t-1) = \begin{bmatrix} A(t-1) & B(t-1) \\ 0 & F(t-1) \end{bmatrix} \quad R_{w_u} = \begin{bmatrix} R_{ww}(t-1) & R_{wn}(t-1) \\ R_{nw}(t-1) & R_{nn}(t-1) \end{bmatrix}$$

and

$$C_u(t) = [C(t) \mid 0]$$

This model can be simplified by choosing $F = I$; that is, u is a piecewise constant. This model becomes valid if the system is oversampled (see [14] for details). The *MBP* for this problem is the standard *Kalman filter* Bayesian algorithm with the augmented matrices given by the equations:

State prediction: $\hat{X}_u(t|t-1) = A_u\hat{X}_u(t-1|t-1)$

Innovation: $e(t) = y(t) - \hat{y}(t|t-1)$ where $\hat{y}(t|t-1) = C_u\hat{X}_u(t|t-1)$

State correction: $\hat{X}_u(t|t) = \hat{X}_u(t|t-1) + K(t)e(t)$

with $K(t)$, the Kalman gain calculated using the inherent state error and innovations covariance matrices where $X_u(t|t) := E\{X_u(t)|Y_t\}$, that is, the conditional mean estimate of the augmented state given all of the previous data up to time t. Note that this is an optimal estimator under Gaussian assumptions (see Candy[13] for details).

One approach to estimating the unknown input sequence, $u(t)$ is to use a Taylor-series representation,[12?] given by

$$u(t + \triangle T) = \alpha_0 + \alpha_1 \left(\frac{\triangle T}{1!}\right) + \alpha_2 \left(\frac{\triangle T^2}{2!}\right) + \text{H.O.T.} \tag{8}$$

where $\alpha_i = \frac{d^i u(t)}{dt^i}$ for $u(t+\triangle T) \approx \sum_i \alpha_i \left(\frac{\triangle T^i}{i!}\right)$. pulse shaper); and (ii) the pre-amplifier. In case (i) we assume all of the required information about the *EMS* is available at the output of the pulse shaping circuitry and the quantifier (A/D) merely extracts the maximum amplitude of the Gaussian shaped pulse and corresponding arrival times, $[\{\xi_i\}, \{\tau_i\}]$. However, we also consider case (ii) where we measure the output of the pre-amplifier (separately). Here the energy deposited by the γ-ray and subsequent charge curves reveal more detailed information about the photon physics (arrival times, multiple arrivals etc.). We digitize the actual pre-amplifier output generating a time series of the pulse and then perform the deconvolution to extract an "enhanced" γ-ray pulse as discovered through the recovered (deconvolved) charging curve leading to the enhanced *EMS*. Once the *EMS* is deconvolved, it can be extracted (amplitudes and arrivals), counted or employed as the input to a parameter estimator capable of providing an improved energy estimate and corresponding arrival time while minimizing the noise and uncertainty.

In this paper we concentrate on the model and deconvolved *EMS*. We accomplish the deconvolution by performing a system identification[13] of both pre-amplifier and pulse shaper to obtain transfer function estimates and then incorporate these estimates in the deconvolution algorithm. In this manner we will eventually be able to construct the final Bayesian sequential processor.

5. RESULTS

In this section we discuss the results of developing the models for both pre-amplifier and pulse shaper and applying them to perform the deconvolution operation. We injected a set of pulse into both systems individually obtaining the required transfer function and then developed the physics-based deconvolution processor as discussed in the previous section.

The test of the algorithm is on a simulated cobalt *EMS* with 1.17 and 1.33 MeV lines generating the random detector input sequence. Here we convolved the simulator output (deposited energy) with the identified composite transfer function. The results are shown in 5 where we see the transfer function validation run in (a) and the actual deconvolution processor in (b). The processor is capable of extracting the *EMS* successfully and improving the overall γ-ray spectrum significantly as shown in Fig. 6. In (a) we see the "true" spectrum indicating two sharp energy lines at the correct energies (1.17 and 1.33 MeV), (b) the estimated (deconvolved) spectrum has captured the line with some uncertainty (spreading shown) but its performance is quite reasonable and demonstrates the enhancement as observed from the measured spectrum of (c). Thus, the Bayesian deconvolver works quite well on the synthesized data set.

Next we performed a controlled experiment where we injected a known "pulse" synthesizing a photon arrival into the preamplifier of the detector system. In 7 (a) we see the results of the Bayesian deconvolution processor capable of extracting the excitation pulse with the corresponding histograms shown in (b)—again a very good agreement demonstrating its performance. As a by-product of the processor we are able to produce an enhanced estimate of the actual raw measurement which we show in (c) agreeing quite closely with the corresponding histograms confirming this result in (d). Thus, it appears that the processor can reliably extract the input excitation using this physics-based approach. Next we summarize and discuss our future work.

6. SUMMARY

We have shown that a physics-based Bayesian processor can be constructed that is capable of extracting the event-mode sequence (*EMS*) from both simulated and measured data sequences. We demonstrated the Bayesian deconvolution processor performance and show that it provides considerable enhancement over the raw data sets providing an enhanced histogram. Our future efforts are aimed at acquiring *EMS* from Cesium, Cobalt and combined radionuclide while incorporation motion into the point source location (e.g. cargo container motion) to observe the tracking capability of the near real-time processor. Our future efforts will also include the construction of the full Bayesian scheme and sequential detection of threat radionuclides using sequential Bayesian processors[14 −].[20]

REFERENCES

1. S. Labov et. al.,"Foundations for Improvements to Passive Detection Systems, LLNL Report, UCRL-TR-207129, 2004.
2. E. Smith et. al., "Enabling Technologies for Passive Radiation Detection, PNNL Report, PNNL-14789, 2004.
3. S. Labov, "Radiation Detection on the Front Lines, Scien. Technol. Review, LLNL, Sept. 2004.
4. R. D. Evans, *The Atomic Nucleus.* (New York, N.Y.: McGraw-Hill, 1985).
5. G.F. Knoll, *Radiation Detection and Measurement, 3rd Ed.,* (Hoboken N.J.: John Wiley, 2000).
6. A. Doucet and P. Duvaut, Bayesian estimation of state space models applied to deconvolution of Bernoulli-Gaussian processes, Signal Process., Vol. 57, 1997.
7. C. Andrieu, E. Barat and A. Doucet, Bayesian deconvolution of noisy filtered point processes, *IEEE Trans. Sig. Proc.*, Vol. 49, 2001.
8. S. Gulam Razul, W. J. Fitzgerald and C. Andrieu, Bayesian model selection and parameter estimation of nuclear emission spectra using RJMCMC, Nucl. Instrum. And Methods in Physics Res. A, Vol. 497, 2003.
9. D. L. Snyder and M. I. Miller, *Random Point Process in Time and Space.* (New York: Springer-Verlag, 1991).
10. A. Meyer, M. Axelrod, J. Candy, K. Sale, D. Slaughter and S. Putkin, "Systematic approach to gamma ray detection," **LLNL Report**, (in progress), 2006.

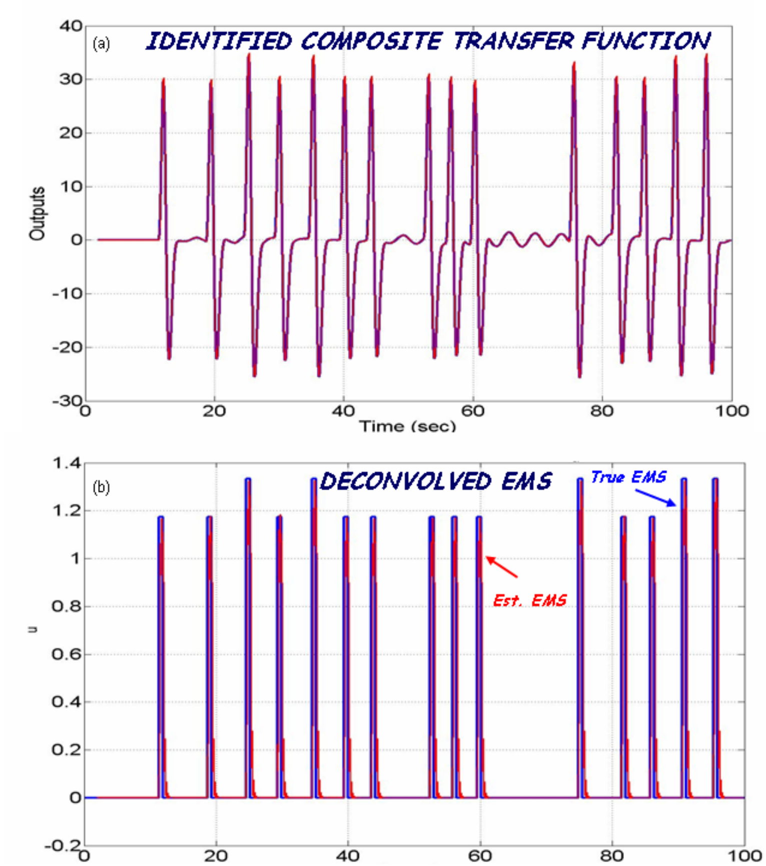

Figure 5. Bayesian Deconvolution Processor Design. (a) System identification of composite (pre-amplifier and pulse shaper) system. (b) Deconvolution processing using identified transfer function with synthesized (known) *EMS* (Cobalt: 1.17 and 1.33 MeV lines).

11. J. M. Mendel, *Maximum Likelihood Deconvolution*, (New York: Springer-Verlag, 1990.
12. J. V. Candy and J. E. Zicker, "Deconvolution of noisy transient signals: A Kalman filtering application," *Proc. IEEE CDC Confr.* and *LLNL Report*, UCID-87432, 1982.
13. J. V. Candy, *Model-Based Signal Processing*, John Wiley: New Jersey, 2006.
14. A. Doucet, N. de Freitas and N. Gordon, *Sequential Monte Carlo Methods in Practice*, Springer-Verlag: New York, 2001.
15. J. Liu, *Monte Carlo Strategies in Scientific Computing*, Springer-Verlag: New York, 2001.
16. S. Godsill and P. Djuric, "Special Issue: Monte Carlo methods for statistical signal processing." *IEEE Trans. Signal Proc.*, vol. 50, 2002.
17. M. S. Arulampalam, S. Maskell, N. Gordon and T. Clapp. tutorial on particle filters for online nonlinear/non-gaussian Bayesian tracking, *IEEE Trans. Sig. Process.*, Vol. 50, 2, 2002.
18. P. Djuric, J. Kotecha, J. Zhang, Y. Huang, T. Ghirmai, M. Bugallo and J. Miguez, "Particle Filtering." *IEEE Signal Proc. Mag.* vol. 20, No. 5, pp. 19-38, 2003.
19. B. Ristic B., S. Arulampalam and N. Gordon, *Beyond the Kalman Filter: Particle Filters for Tracking Applications*, Boston: Artech House, 2004.
20. A. Doucet and X. Wang, "Monte Carlo methods for signal processing," *IEEE Signal Proc. Mag.* vol. 24, No. 5, pp. 152-170, 2005.

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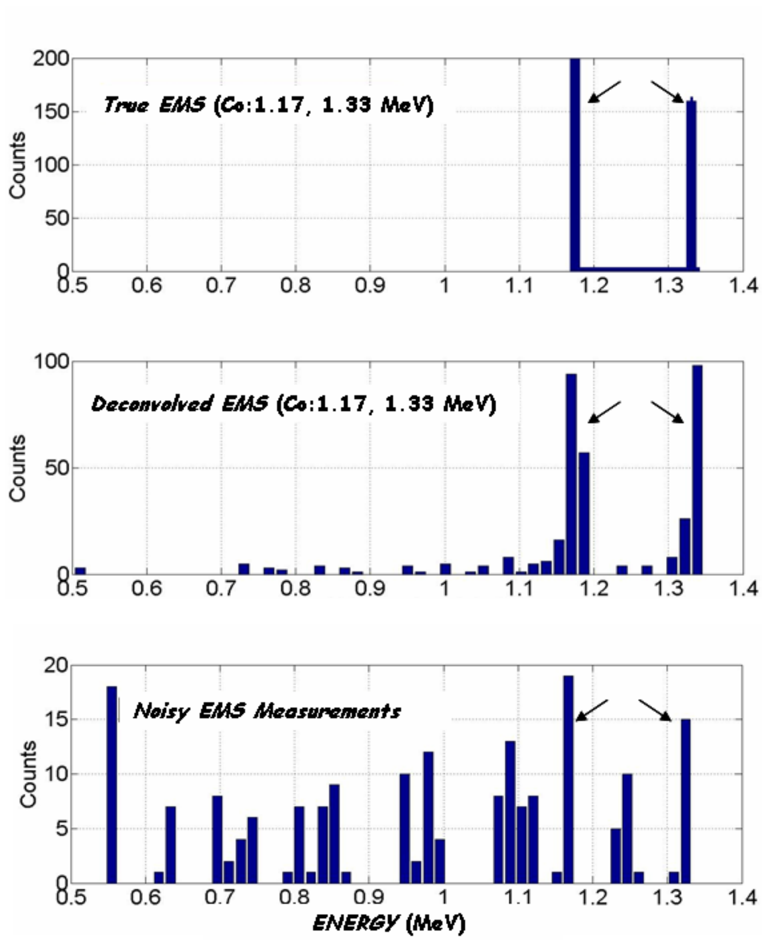

Figure 6. Deconvolution Processor Performance/Enhancement (Cobalt: 1.17 and 1.33 MeV lines). (a) Histogram of True *EMS* (synthesized). (b) Processed *EMS* histogram. (c) Raw (synthesized) measured detector output histogram.

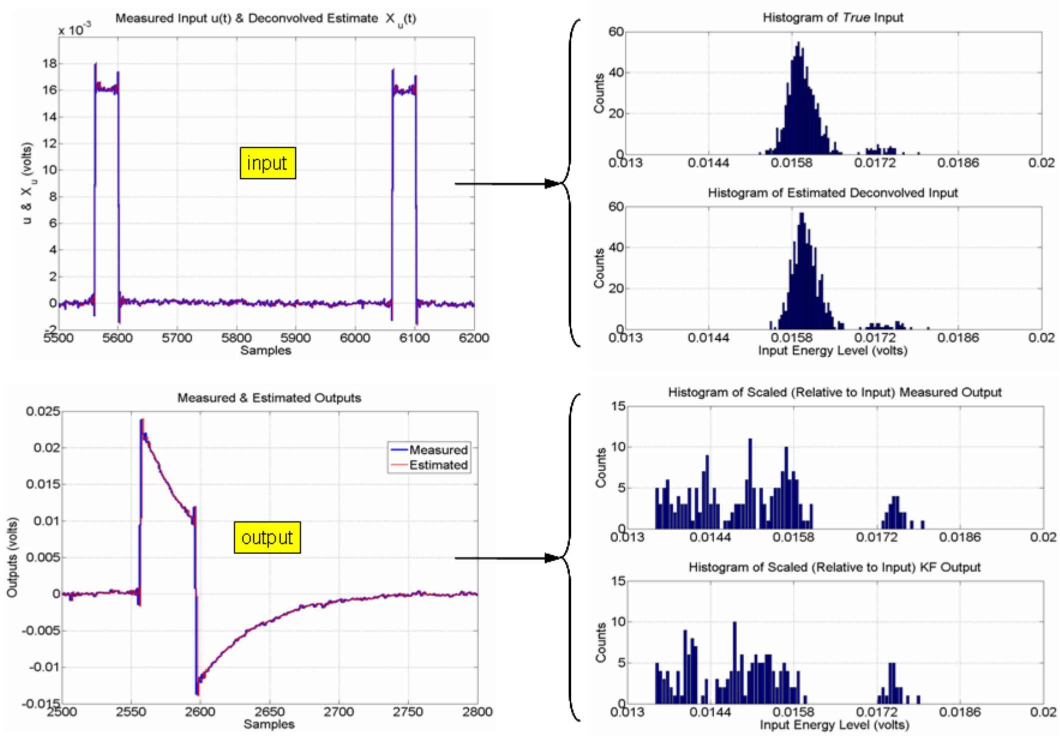

Figure 7. Experimental Bayesian Deconvolution Processor Outputs. (a) Actual test input excitation pulse sequence and estimated (deconvolved) input. (b) True and estimated (deconvolved) input excitation histograms. (c) Measured and estimated preamplifier outputs. (d) Measured and estimated output histograms.