A Sequential Bayesian Bio-Inspired Approach for Fast Radionuclide Identification

Preliminary results

NeuroSTIC Day’s – June 23rd and 24th; 2016 INRIA MONTBONNOT
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NeuroSTIC Day’s – June 23rd and 24th; 2016 INRIA MONTBONNOT
1. Introduction
   1. Context and motivations
   2. Background
   3. Problematic

2. Proposed approach
   1. Traditional neural network
   2. Spiking neural network approach
   3. Bayesian approach

3. Implementation
   1. Experiments and results
   2. Theoretical results
   3. Experimental results

4. Conclusion and perspectives
INTRODUCTION: CONTEXT AND MOTIVATIONS

• Nuclear and Radiological threats:
  • Nuclear matterial traffic [1-3] (NTP) (neutron emitters)
  • Radioactive matterial traffic/transport
  • Dirty bomb

→ Terrorism
INTRODUCTION: CONTEXT AND MOTIVATIONS

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→ Terrorism

Two kinds of menace:

• Fissile materials trade is strictly controlled by the non-proliferation treaty (NTP), but some countries try to illegally import them. Fissile materials are neutron emitters.

• Most of radionuclides can be employed to fill a dirty-bomb and used by terrorists. Many radionuclide emmit gamma rays. Threats must quickly identified and discriminated from natural radioactivity.
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FAST IDENTIFICATION OF RADIONUCLIDES IS CRUCIAL

1) Detection in public transport infrastructure
   - Train, Highway, airport, harbour etc.

2) Special operation forces
   - unknown operation ground

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Drone 'containing radiation' lands on roof of Japanese PM's office

Traces of radiation reportedly detected on drone carrying camera and bottle with unidentified contents
Radionuclides emit gamma rays (photons)

**Fissile materials emit neutrons and gamma rays**

Natural and legitimate radionuclides are everywhere and emit gamma rays

→ **Natural or legitimate gamma emitters can be used to hide a threat (In a cargo for example)**

Industrial and medical waste can be radioactive and used to hide dirty bomb materials

> **60 Natural, medical and industrial legitimate nuclides**

- K40 concrete; banana and potatoes 150 Bq/kg, brazil nuts 244Bq/kg, Tea 770bq/Bg, Soya 440 Bq/kg
- Argon (stones)
- Am241 (smoke detectors)
- Radon (gas) (stones)
- Radium 226 Am241 (lightening rodes)
- Thorium (60-70ies camera lenses, soldering bars)

Ex:

30 tons of soya → 13.2 Mbq
1g U238 → 12434 bq

High chemical toxicity if ingerted (max acceptable 0.6µg/kg body weight per day)
**Approach to detect gamma rays:**

A gamma ray interacts with the material of the detector, a part of its energy is deposited into the detector. This energy deposit is detected.

A pulse voltage variation is measured for each gamma energy deposit.

- **Scintillators emit visible-range photons**
  - Photomultiplier (PM) amplifies the light, and converts it to a current/voltage variation

- **Semi-conductor detector**
  - Current/voltage variation readout
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1) Pulses are extracted from the signal

1) Baseline removal, thresholding etc.

Figure 2: original signal after BLR
INTRODUCTION: BACKGROUND

1) Pulses are extracted from the signal
   1) Baseline removal, thresholding etc.

2) Pulses are analysed
   to extract a pseudo-energy feature
   1) Amplitude
   2) Pulse area
   3) ...

Figure 2: original signal (top) and extracted pulses (bottom)
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   1) Baseline removal, thresholding etc.

2) Pulses are analysed
   to extract a pseudo-energy feature
   1) Amplitude
   2) Pulse area
   3) …

3) « pseudo-energy » is correlated to the energy deposit of the emitted photon
   1) Pre-calibration with well-known radionuclide is required to match pseudo-energy and real energy

Figure 2 : original signal (top) and extracted pulses (bottom)
How to identify a radionuclide? Gamma spectrometry

Build the histogram of pulses pseudo-energy (def. acquisition time)

Unique signature of a radionuclide visible in a spectrum

Gamma spectrometry requires:

Acquisition of a large number of pulses (millions of counts)
**How to identify a radionuclide?** Gamma spectrometry

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Spectrum: unique signature of a radionuclide

Gamma spectrometry requires:

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- High-resolved detector (in terms of resolution)
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Table I: Energy resolution for different detector class

<table>
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<tr>
<th>Class of detector</th>
<th>Energy range &amp; resolution</th>
<th>Required ADC resolution</th>
<th>Count rate (before pile-up)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gas</td>
<td>10 eV – 7 MeV, ± 2 - 50 keV</td>
<td>8 – 13 bits</td>
<td>$10^3 – 10^8$ cps</td>
</tr>
<tr>
<td></td>
<td>3 keV – 10 MeV, ± 100 - 300 eV</td>
<td>&gt;16 bits</td>
<td>$10^7$ cps</td>
</tr>
<tr>
<td>Organic Scintillator</td>
<td>0 – 4 MeV, ± 1 - 40 keV</td>
<td>7 – 14 bits</td>
<td>$10^7 – 10^8$ cps</td>
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<td></td>
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<td>Semiconductor</td>
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<td>&gt;16 bits</td>
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Figure 3: simplified view of a spectrum construction

Figure 4: Energy resolution for different detector classes
INTRODUCTION : PROBLEMATIC AND GOALS

- Identification of mixtures
  ie. a threat hidden inside a legitimate radioactive products cargo

- Multi-detector, low-area, low-resolution low-cost detectors
  Nal, Plastic scintillators, CZT

- Low-count rate
  Mobile and/or shielded radioactive sources
  → Max 500 counts to make the identification (few seconds)

  → Spectrum construction is impossible

  → Peak based identification is impossible

- Adaptivity to the background-noise

Figure 5 : Spectra of individual radionuclide (b-d) and for a mixture (a)
High Resolution Germanium detector – source IAEA [8]
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Known to be efficient for classification problems [20].

Figure 6: Illustration of a single neuron, the weights, summing and activation (perceptron)
Known to be efficient for classification problems [20].

\[ \text{output} = \begin{cases} 
1 & \text{if } \sum_{i=0}^{n} w_i x_i > 0 \\
-1 & \text{otherwise}
\end{cases} \]

\[ \sum_{i=0}^{n} w_i x_i = w \cdot x \]

**Figure 6**: Illustration of a single neuron, the weights, summing and activation (perceptron).

**Figure 7**: single-layer neural-network (top) and multi-layer neural-network (bottom).
THE PROPOSED APPROACH : RELATED WORKS

Known to be efficient for classification problems [20].

Traditional approaches [9-10] :

1) Train neural network with one-radionuclide gamma spectra weights

2) Acquire a proper spectrum of the sample to analyze

3) Use the acquired spectrum as input of the neural network

→ Approach works very well with one-radionuclide

Can identify simple mixtures components

Long acquisition time

High resolution detector ([10] uses HPGe)

No reliable quantitative results (proportion)

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Instead of transmitting numerical values (int, float) between neurons, information is encoded using spikes (pulses train).

*Biology: « observed » in 1926, Adrian and Zotterman (frog skin), du Bois-Reymond 1848, Schuetze 1983, Kandel et al. 1ressure.*

*Figure 8 : Spike observation on a biological neuron [11]*
THE PROPOSED APPROACH : PROPOSED APPROACH

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Pressure.

Figure 8 : Spike observation on a biological neuron [11]

![Spike Observation](image)

Dendrite 1

Dendrite 2

Figure 9: Train observation of the Dendrites of a neuron (input)

Code: timings, frequency, combinations of inputs encodes the information. Many schemes were proposed to encode the informations.

![Train Observation](image)
THE PROPOSED APPROACH: PROPOSED APPROACH

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| Figure 9: Train observation of the Dendrites of a neuron (input) |

Code: timings, frequency, combinations of inputs encodes the information. Many schemes were proposed to encode the informations.

→ Pulses acquired by a radiation detector ≈ spikes
One Spike per event per channel (pseudo-energy $i$).

The structure of the unitary neuron is modified.

We attach a neuron counter $C_k$ to each identification neuron and replace summing and function by Bayes’ formulas to get posterior probabilities (1) and prior probabilities (2).

$$Pr(A_k|i) = \frac{Pr(A_k).Pr(i|A_k)}{\sum_1^n Pr(A_j).Pr(i|A_j)} = \frac{Pr(A_k).w_{ik}}{\sum_1^n Pr(A_j).w_{ij}} \quad (1)$$

$$Pr(A_k) = \frac{C_k}{\sum_1^n C_j} \quad (2)$$
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\]

\[
Pr(A_k) = \frac{C_k}{\sum_1^n C_j} \tag{2}
\]

If activation function fires, then quantitative results are given by $Pr(A_k)$

$Pr(A_k|i)$ is used for identification

Figure 10 : Simplified view of the proposed topology
Learning is not required: $W_{ij}$ are directly given by the spectra of radionuclides to identify.

Spectra can be built using the same acquisition chain.

No energy calibration is required.

No characterization of the acquisition chain.

Iterative approach, the result is refined gradually with new incoming events.
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Three experiments performed, low-count (<150 and <1000):

1) Theoretical ideal:
   ideal detector simulated, synthetic data

2) Theoretical data, real-world simulation:
   non-ideal NaI detector, synthetic data, no background noise

3) Real detector and real radioactive sources:
   Well-type NaI detector, by CEA LNHB-LNE
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   6 radionuclides: $^{241}$Am, $^{133}$Ba, $^{207}$Bi, $^{57}$Co, $^{60}$Co, $^{137}$Cs and $^{40}$K
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Figure 11: Implementation of the proposed approach
Radionuclides selection: (ISO 22188:2004) (IAEA NSS1 2010) and (ANSI N42.38-2006) : 6 radionuclides: $^{241}\text{Am}$, $^{133}\text{Ba}$, $^{207}\text{Bi}$, $^{57}\text{Co}$, $^{60}\text{Co}$, $^{137}\text{Cs}$ and $^{40}\text{K}$
# Experiments and Results: Synthetic Data

## Ideal and Non-Ideal theoretical data (NaI detector simulated) 150 TOTAL pulses

<table>
<thead>
<tr>
<th>Radionuclide</th>
<th>Ideal</th>
<th>Convolled</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Am241</td>
<td>0,04%</td>
<td>0,04%</td>
<td>0,00%</td>
</tr>
<tr>
<td>Ba133</td>
<td>0,03%</td>
<td>0,03%</td>
<td>0,00%</td>
</tr>
<tr>
<td>Co60</td>
<td>0,03%</td>
<td>0,03%</td>
<td>0,00%</td>
</tr>
<tr>
<td>K40</td>
<td>0,03%</td>
<td>0,03%</td>
<td>0,00%</td>
</tr>
<tr>
<td>Co57</td>
<td>99,83%</td>
<td>99,83%</td>
<td>0,00%</td>
</tr>
<tr>
<td>Cs137</td>
<td>0,03%</td>
<td>0,03%</td>
<td>0,00%</td>
</tr>
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<tr>
<td>Am241</td>
<td>0,05%</td>
<td>0,04%</td>
<td>0,01%</td>
</tr>
<tr>
<td>Ba133</td>
<td>0,07%</td>
<td>0,32%</td>
<td>-0,25%</td>
</tr>
<tr>
<td>Co60</td>
<td>0,03%</td>
<td>0,03%</td>
<td>0,00%</td>
</tr>
<tr>
<td>K40</td>
<td>0,03%</td>
<td>0,03%</td>
<td>0,00%</td>
</tr>
<tr>
<td>Co57</td>
<td>50,05%</td>
<td>49,84%</td>
<td>0,21%</td>
</tr>
<tr>
<td>Cs137</td>
<td>49,76%</td>
<td>49,74%</td>
<td>0,03%</td>
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<tr>
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<td>32,78%</td>
<td>33,89%</td>
<td>-1,11%</td>
</tr>
<tr>
<td>Ba133</td>
<td>33,47%</td>
<td>32,62%</td>
<td>0,84%</td>
</tr>
<tr>
<td>Co60</td>
<td>0,03%</td>
<td>0,09%</td>
<td>-0,06%</td>
</tr>
<tr>
<td>K40</td>
<td>33,30%</td>
<td>33,24%</td>
<td>0,06%</td>
</tr>
<tr>
<td>Co57</td>
<td>0,27%</td>
<td>0,04%</td>
<td>0,23%</td>
</tr>
<tr>
<td>Cs137</td>
<td>0,15%</td>
<td>0,12%</td>
<td>0,04%</td>
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EXPERIMENTS AND RESULTS : SYNTHETIC DATA

Non-Ideal theoretical data (NaI detector simulated) : plot $Pr(A_k)$ for 1000 TOTAL pulses

Figure 13 : Plot of $Pr(A_k)$ for 1000 pulses Am-241, Ba-133, Co-60, Cs-137 and K-40 20% mixture
Non-Ideal theoretical data (NaI detector simulated): plot $Pr(A_k)$ for 1000 TOTAL pulses

Figure 14: Plot of $Pr(A_k)$ for 1000 pulses Am-241 and Co-60 50% mixture
EXPERIMENTS AND RESULTS: REAL MIXTURES

Real dataset (5 radionuclides) 152 and 1002 counts:

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Am241</td>
<td>0,03%</td>
<td>0</td>
<td>0,04%</td>
<td>0</td>
</tr>
<tr>
<td>Ba133</td>
<td>0,13%</td>
<td>0</td>
<td>0,43%</td>
<td>4</td>
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<tr>
<td>Bi207</td>
<td>0,66%</td>
<td>1</td>
<td>1,12%</td>
<td>11</td>
</tr>
<tr>
<td>Co60</td>
<td>99,12%</td>
<td>151</td>
<td>98,30%</td>
<td>985</td>
</tr>
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<td>Cs137</td>
<td>0,06%</td>
<td>0</td>
<td>0,11%</td>
<td>1</td>
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Uncertainty is caused by the intrinsic random nature of the events.
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<td>Bi207</td>
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<td>276</td>
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<td>Co60</td>
<td>30,37%</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Nucleide</th>
<th>Percent</th>
<th>Counts</th>
<th>Percent</th>
<th>Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Am241</td>
<td>0,49%</td>
<td>1</td>
<td>0,16%</td>
<td>2</td>
</tr>
<tr>
<td>Ba133</td>
<td>29,49%</td>
<td>45</td>
<td>32,23%</td>
<td>323</td>
</tr>
<tr>
<td>Bi207</td>
<td>29,29%</td>
<td>45</td>
<td>26,27%</td>
<td>263</td>
</tr>
<tr>
<td>Co60</td>
<td>40,14%</td>
<td>62</td>
<td>37,81%</td>
<td>379</td>
</tr>
<tr>
<td>Cs137</td>
<td>0,59%</td>
<td>1</td>
<td>3,53%</td>
<td>35</td>
</tr>
</tbody>
</table>

Uncertainty is caused by the intrinsic random nature of the events.
**EXPERIMENTS AND RESULTS: REAL MIXTURES**

**Real dataset:** plot $Pr(A_k)$ 1002 TOTAL pulses

*Figure 15: Plot of $Pr(A_k)$ for 1000 pulses Am-241, Ba-133, Cs-137 1/3 mixture*
Real dataset: plot $Pr(A_k)$ 1002 TOTAL pulses

Figure 16: Plot of $Pr(A_k)$ for 1000 pulses
Am-241, Ba-133, Bi-207, Cs-137 1/4 mixture
Better results in offline mode:

An offline variant of the algorithm processes complete pre-acquired spectrum:

→ *Slight* reduction of the bias

**Table XIII : results obtained with an offline variant of the approach**

<table>
<thead>
<tr>
<th>Counts</th>
<th>$^{60}$Co / 0.35</th>
<th>$^{133}$Ba / 0.15</th>
<th>$^{137}$Cs / 0.15</th>
<th>$^{207}$Bi / 0.35</th>
<th>$^{241}$Am / 0</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0.360 (68)</td>
<td>0.134 (68)</td>
<td>0.162 (78)</td>
<td>0.326 (93)</td>
<td>0.018 (24)</td>
</tr>
<tr>
<td>100</td>
<td>0.365 (65)</td>
<td>0.137 (48)</td>
<td>0.146 (61)</td>
<td>0.34 (7)</td>
<td>0.011 (12)</td>
</tr>
<tr>
<td>200</td>
<td>0.367 (58)</td>
<td>0.149 (40)</td>
<td>0.146 (44)</td>
<td>0.329 (59)</td>
<td>0.009 (13)</td>
</tr>
<tr>
<td>500</td>
<td>0.356 (39)</td>
<td>0.143 (24)</td>
<td>0.147 (28)</td>
<td>0.345 (41)</td>
<td>0.008 (7)</td>
</tr>
<tr>
<td>1000</td>
<td>0.358 (24)</td>
<td>0.148 (19)</td>
<td>0.145 (24)</td>
<td>0.343 (28)</td>
<td>0.007 (6)</td>
</tr>
<tr>
<td>5000</td>
<td>0.352 (12)</td>
<td>0.149 (8)</td>
<td>0.148 (11)</td>
<td>0.346 (16)</td>
<td>0.005 (4)</td>
</tr>
<tr>
<td>10000</td>
<td>0.352 (8)</td>
<td>0.150 (5)</td>
<td>0.149 (7)</td>
<td>0.345 (8)</td>
<td>0.003 (2)</td>
</tr>
</tbody>
</table>

This variant is maybe usable with other class of spectrometry: RAMAN, IR-VIS-UV etc.
Current developments

A variant is under development:

- continuous analysis of the accumulated spectrum.
- « A leak » is attached to each neuron, which provides a faster convergence

→ Better results are expected (obtained), especially on plastic scintillator.

Design and integration of a fully functional embedded prototypes

• 125MHz for slow plastic scintillators and NaI detectors (winter 2016)
• 500MHz for plastic scintillators: under progress (2017)
• 4GHz for fast plastic scintillators: under progress (2017)

Neutron Gamma discrimination to detect fissile materials
Current developments

A variant is under development:

- continuous analysis of the accumulated spectrum.
- « A leak » is attached to each neuron, which provides a faster convergence

→ Better results are expected (obtained), especially on plastic scintillator.
1. Introduction
   1. Context and motivations
   2. Background
   3. Problematic

2. Proposed approach
   1. Traditional neural network
   2. Spiking neural network approach
   3. Bayesian approach

3. Implementation
   1. Experiments and results
   2. Theoretical results
   3. Experimental results

4. Conclusion and perspectives
CONCLUSION AND PERSPECTIVES

Highlights

- A fast embeddable real-time radionuclide identification applicable in spectroscopic portal monitors is presented.
- The proposed algorithm combines a Bayesian approach and a spiking neural network.
- The approach was validated using the mixture of gamma-emitter spectra provided by a well-type NaI(Tl) detector. Now validated on plastic scintillator.
- No energy calibration required, no apriori knowledge on the detector is required.
CONCLUSION AND PERSPECTIVES

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- The proposed algorithm combines a Bayesian approach and a spiking neural network.
- The approach was validated using the mixture of gamma-emitter spectra provided by a well-type NaI(Tl) detector. Now validated on plastic scintillator.
- No energy calibration required, no apriori knowledge on the detector is required.

**Perspectives**

- Test the approach using different class of detectors: (validated on HPGe and NaI)
- Low-cost plastic scintillators, CZT and SDD planned.
- Integration in a Radiation Portal Monitor; environment monitoring;
- Survey/Comparison with peak-based approach.
REFERENCES