Radio-isotope Identification Using Dictionary Learning Approach for Plastic γ Spectra

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1. Introduction

A plastic scintillator has been widely used as a radiation portal monitor (RPM) for homeland security deployed at airports, seaports, and border crossing to detect illegal radioactive materials. To adequately identify variable radio-isotopes, it should contain an advanced spectroscopic processing to overcome its inherent low resolution and absence of photoelectric peaks. Our focus is the radio-isotope identification (RIID) for γ spectra obtained from the plastic scintillation detector. Many algorithms including region of interest, energy windowing, and inverse calibration matrix algorithm has been intensively studied for RIID of γ spectra. Recently, algorithm using machine learning such as artificial neutral network, principle components analysis, and so forth has been implemented into RIID and shown the outstanding performance [1].

Compressive sensing (CS) is an advanced sampling theory with efficiently acquiring signals than Nyquist-Shannon sampling theorem by solving sparse coefficient. The basic structure of CS theory could be expressed as Eq. (1).

$$\mathbf{Y} = \mathbf{DX} \tag{1}$$

where $\mathbf{Y}\in\mathbb{R}^{M\times N}$ is a matrix consisting of measured data, $\mathbf{D}\in\mathbb{R}^{M\times K}$ is a overcomplete matrix ($K \gg M$) called dictionary, and $\mathbf{X}\in\mathbb{R}^{K\times N}$ is a sparse matrix. The very dictionary indicates a proper representation basis of data sets by means of reduced dimensionality subspaces, which can be adaptive to both the input signal and the processing tasks. Fourier, discrete cosine, and wavelet basis are commonly used as a predescribed dictionary for signal reconstruction. In fact, these prespecified dictionary could not be suitable for sparse representation of γ spectra because the spectra show a variant of different Gaussian distribution in each measurement.

In this work, dictionary learning as a supervised learning approach was proposed and applied to RIID for plastic (EJ-200) γ spectra. Label consistent K-SVD (LC-KSVD) algorithm was exploited to adapting the dictionary to a given training spectra, **Y** [2-3]. Labels shown in Table I were made by combining radio-isotopes (^{133}Ba, ^{22}Na, ^{137}Cs, ^{60}Co). To find such an optimized dictionary and test its performance, Monte Carlo simulation and experimental measurement was carried out.

2. Methods and Results

2.1 Discriminative dictionary through LC-KSVD

With the regard to efficient classification, a discriminative dictionary tailored to given training γ spectra samples **Y** should be learned. LC-KSVD algorithm was exploited to learn a both reconstructive and discriminative dictionary. LC-KSVD consists of three error term. First one is the reconstruction error; another one denotes the discriminative sparse code error; the last one indicates the classification error. Eq. (2) shows the objective function of the LC-KSVD.

$$\langle \mathbf{D},\mathbf{W},\mathbf{A},\mathbf{X}\rangle = \arg\min\{\|\mathbf{Y}-\mathbf{DX}\|_2^2 + \alpha\|\mathbf{Q}-\mathbf{AX}\|_2^2 + \beta\|\mathbf{H}-\mathbf{WX}\|_2^2\}$$
$$\text{s.t. } \|x_i\|_2 \le T_0, \text{ for } i = 1, 2, \ldots, N \tag{2}$$

where $\|\mathbf{S}\|_p$ is the l_p-norm of a matrix **S**, $\mathbf{Q}\in\mathbb{R}^{K\times N}$ is the discriminative sparse code corresponding to an input spectrum, $\mathbf{A}\in\mathbb{R}^{K\times K}$ is a linear transformation matrix to force the sparse code to be discriminative, $\mathbf{H}\in\mathbb{R}^{m\times N}$ is the class label matrix of input spectra, $\mathbf{W}\in\mathbb{R}^{m\times K}$ is the classifier, m is the number of label, and T_0 is the degree of sparsity. Both α and β are a regression constant of controlling each term. Eq. (2) could be solved through K-SVD algorithm, which is generalization of K-means clustering. K-SVD is iteratively alternating algorithm between sparse coding and updating atoms of the dictionary [4]. This process is conducted to all terms in Eq. (2) simultaneously, enforcing the input spectra of the same label to be represented by similar sparse code.

2.2 Samples for dictionary learning

To tailor the dictionary to various spectra, learning samples were generated by Monte Carlo simulation, MCNP6. Similarly simulating the measured spectrum, MCNP6 provides a Gaussian energy broadening (GEB) effect on each energy bin based on Eq. (3).

$$\text{FWHM} = a + b(E + cE^2)^{1/2} \tag{3}$$

To approximately compute values of three coefficient (a, b, c), full width half maximum (FWHM) for the corresponding photo-peak energy is required through the preliminarily measured spectrum. However, no photo-peak appears due to the inherent property of the plastic. To overcome this difficulty, an iterative method using Compton maximum and Compton edge instead of the photo-peak was used [5]. Fig. 1 shows the both the measured and the simulated spectrum of ^{22}Na. Based on this setup, 200 samples per each label was produced

with the number of particle histories in the range from 1.0E+04 to 1.0E+07.

Table I: Details of label for the corresponding radio-isotope

Label #	Isotopes					Remarks
	BG	^{133}Ba	^{22}Na	^{137}Cs	^{60}Co	
1	o	-	-	-	-	No RI
2	o	o	-	-	-	RI (#1)
3	o	-	o	-	-	
4	o	-	-	o	-	
5	o	-	-	-	o	
6	o	o	o	-	-	RI (#2)
7	o	o	-	o	-	
8	o	o	-	-	o	
9	o	-	o	o	-	
10	o	-	o	-	o	
11	o	-	-	o	o	
12	o	o	o	o	-	RI (#3)
13	o	o	o	-	o	
14	o	o	-	o	o	
15	o	-	o	o	o	
16	o	o	o	o	o	RI (#4)

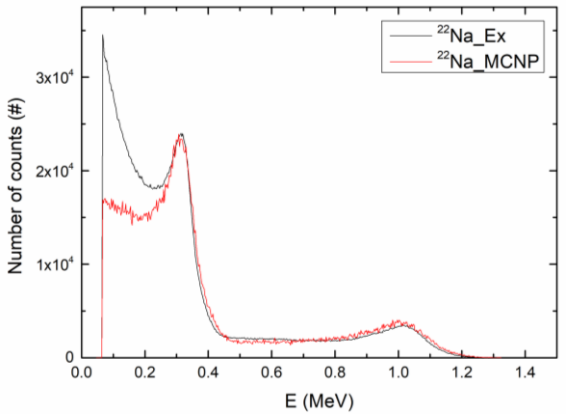

Fig. 1. Measured and simulated energy spectrum with ^{22}Na

2.3 Results

Dictionary coupled with classifier was simultaneously learned with simulated and measured spectra. Size of dictionary atom, *K* was 3200 to be easily overcompleted matrix, which also made the dimension of energy bin, *M* be set 512. Regression constants (α, β) and sparsity (T_0) were arbitrarily set to 2, 4 and 1. γ spectra were measured for 1 sec intervals from 1 to 10 sec with respect to Table I. γ spectra obtained from the distance (5 cm and 10 cm) were used as learning and testing samples of dictionary respectively. Fig. 2 showed the confusion matrix for dictionary training with only simulated data, while Fig. 3 indicated the one for dictionary adapting to the measured data. The average accuracy of each case was 43.3% and 89.4%. The second one had considerably accurate prediction except the two classes. This implied that the measured samples should be included in learning samples for high accuracy. In the future work, to achieve an advanced discriminative dictionary, optimization process of user-specified parameters would be considered.

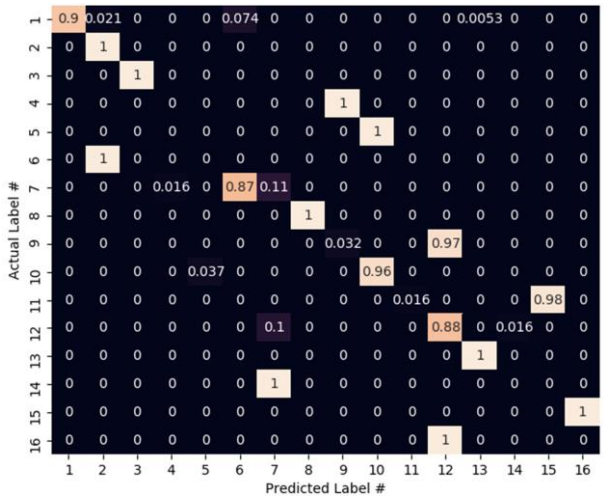

Fig. 2. Confusion matrix for all labels with dictionary learned by simulated samples

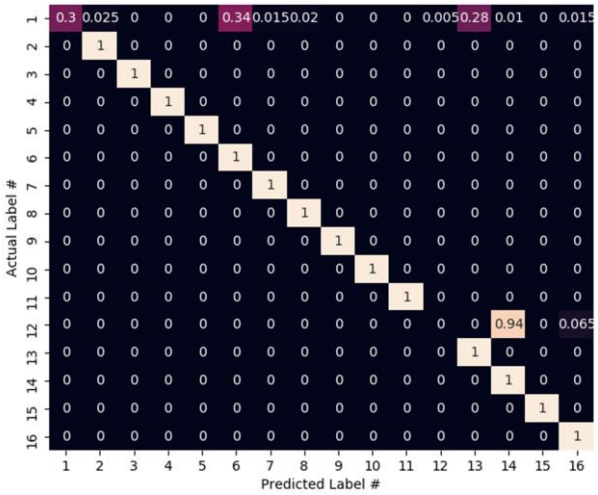

Fig. 3. Confusion matrix for all labels with dictionary learned by measured samples

4. Conclusion

Dictionary learning approach based on LC-KSVD was studied to be applied in classifying plastic γ spectra for RIID. We attempted to generate learning samples via MCNP6 F8 tally with GEB card and experimental measurement. A dictionary adapting to measured data outperformed than another one learned with only simulated spectra, but there was need to resolve problem for some labels. Hence, further works would be improving the classification error of the discriminative dictionary with changing parameters in the learning step.

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