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Achieving High Resolution Gamma-Ray Spectra Using Spectrum Data Obtained from NaI(Tl) Detector by Multi-Output Regressor-Chain Structure Based on SVR

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A B S T R A C T

This paper proposes a new approach for generating high-resolution energy spectra using cost-effective Sodium iodide Thallium activated (NaI(Tl)) detectors. It employs a multi-output regression chain structure based on support vector regression (SVR) to map NaI(Tl) spectra to their corresponding HPGe spectra. The suggested framework utilizes a regression chain strategy to enhance regression models that lack support for multi-output regression. This involves initially using one regressor for each energy channel of the HPGe spectrum. Subsequently, multiple regressors are integrated to predict all energy channels of the HPGe spectrum. Each regressor in the chain receives the entire NaI spectrum as input. Then, for each subsequent regressor, the input is further augmented by concatenating the outputs of all preceding regressors in the chain. Despite being trained on a limited radioisotope library, the model exhibits exceptional performance across diverse measured test spectra containing multiple radioisotopes. Among the various kernel functions employed (linear, radial basis function (RBF), and polynomial), the RBF and polynomial kernels yielded superior performance compared to the linear kernel. By enabling HPGe spectrum prediction using NaI(Tl) detectors, this study highlights a significant advancement in radiation detection capabilities, addressing cost and operational considerations.

Keywords: Multi-output regression; NaI detector; HPGe detector; Gamma spectroscopy; Support vector regression; Radioisotope.

1. Introductions

Gamma-ray spectroscopy is a fundamental technique used in various scientific fields such as nuclear physics, environmental monitoring, and material characterization. It is widely utilized in environmental radiation monitoring, radioactive mineral exploration, radiation therapy, and food safety inspection [1-5]. This method involves analyzing the energy distribution of gamma rays emitted by atomic nuclei, providing valuable formation about their

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composition and structure [6]. HPGe detectors offer excellent energy resolution, allowing them to differentiate between gamma rays with very similar energies. However, their high cost, complex manufacturing process, and the requirement for cryogenic cooling at -196°C (77 K) restrict their widespread use [6]. Sodium iodide Thallium activated (NaI(Tl)) detectors are commonly used due to their high efficiency and cost-effectiveness. Nevertheless, their energy resolution is inferior to that of high-purity germanium (HPGe) detectors [6-8]. This limitation hinders the accurate identification and quantification of closely spaced gamma-ray peaks, especially in complex spectra where energy peaks overlap.

Several methods address the challenge of energy peak overlap in NaI detector gamma spectra, including deconvolution, curve fitting, and wavelet transformation [9-11]. Deconvolution of low-resolution detector spectra, such as those obtained from NaI(Tl) detectors, has long been a significant challenge in gamma spectrometry and various security applications. These approaches often involve complex algorithms with numerous parameters requiring individual optimization for each specific application. Recently, fully connected neural networks (FCNNs) have emerged as a promising alternative due to their relatively simpler computational structures, faster response times, and higher flexibility. FCNNs enable the conversion of spectra acquired with inexpensive and user-friendly NaI detectors into the high-resolution counterparts typically obtained from HPGe detectors [12]. This method eliminates the need for HPGe detectors while transforming spectrum decomposition into a parameter-free, multi-output regression task.

The FCNN model proposed by Saeidi et al [12]. Demonstrated the capability of AI models in recognizing and transforming gamma-ray spectrum patterns from various detectors. However, these constructed spectra exhibit additional peaks. Training such models necessitates the creation of datasets encompassing multiple radioisotope spectra with varying contributions. In another study, a method based on SVR was presented to construct the NaI spectra using plastic spectra, in which single spectra were used for training only [13]. Similarly, this study presents a novel model designed to enhance the predicted HPGe spectrum of multiple radioisotopes solely utilizing their individual spectra. Considering the multi-output regression nature of NaI to HPGe spectrum mapping, a multi-output chain regression architecture is implemented, leveraging the support vector regression machine learning algorithm [14] and employing the problem transformation method [15].

2. Research theories

2.1. Multi-output regression

Multi-output regression is a technique used to predict two or more continuous numerical outcomes simultaneously based on a single input or multiple input instances. One common strategy to achieve this simultaneous prediction is by decomposing the multi-output regression problem into multiple single-output regression problems [15]. A method for implementing this decomposition is the Ensemble of Regressor Chains [16]. This model utilizes several single-output regressors in a sequential manner, where each subsequent regressor's

prediction depends on the outputs of the preceding regressors. The framework of the chained regression model for training and testing is illustrated in Fig. 1. The training process involves using n regressors as follows:

- The first regressor get [x_train] as the input, and t_1 as target, resulting in y_1 as the output and built regressor 1.
- The second regressor get [x_train, y1] as the input, and t_2 as target, resulting in y_2 as the output and built regressor 2.

  ⋮
- The n_{th} regressor get [x_train, y_1, y_2, ..., y_{n-1}] as the input, and t_n as target, Resulting in y_n as the output and built regressor n.

In the context of gamma spectroscopy, $x_{\_train}$ represents the complete NaI spectrum. Each energy channel within the HPGe spectrum is denoted by t_i, with t_1 representing the first channel. Notably, t_1 serves as the target variable for the initial regressor. This pattern systematically extends to all subsequent energy channels (t_2, t_3, ..., t_n) of the HPGe spectrum, where each channel acts as the target variable for a corresponding regressor. Consequently, an HPGe spectrum containing n energy channels, mathematically represented as [t_1, t_2,..., t_{n-1}, t_n], undergoes training using a set of n regressors. As a result, the final model output, corresponding to the predicted HPGe spectrum, is constructed as [y_1, y_2, ..., y_{n-1}, y_n]. During the testing phase, when the model encounters a new, unseen instance ($x_{\_test}$), the n regressors developed during training are utilized to forecast the output, yielding [$\overline{y_1}$ $\overline{y_2}$ ⋯ $\overline{y_n}$].

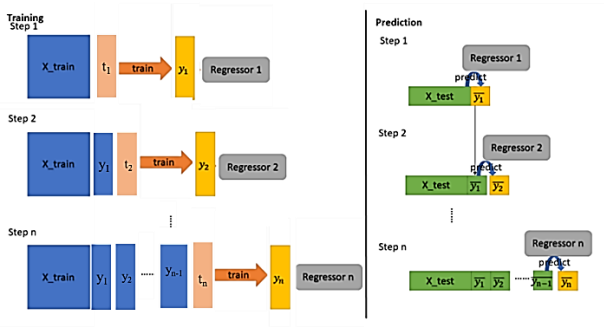

Fig. 1. Regression chain Framework for training and testing steps.

Any machine learning model capable of single-output regression can be adapted for use in this system. Our MIMO system employs Support Vector Regression (SVR) as the single-output regression model. Sánchez-Fernández et al [17]. have investigated the application of SVR to the problem of multiple-input multiple-output (MIMO) frequency-nonselective channel estimation.

Support Vector Regression, a method for tackling regression tasks, was inspired by the Support Vector Machine (SVM) algorithm originally designed for classification problems. SVM, introduced by Vladimir Vepnik in 1963 for linear classification [18], was later extended to nonlinear problems through the kernel trick by Guyan, Vepnik, and et al. in 1992 [19]. Building upon this foundation, Drucker, Vapnik, et al. presented SVR in 1996, adapting the SVM framework to effectively handle regression problems [14].

The overall structure of the SVR algorithm is depicted in Fig. 2. SVR addresses nonlinear regression problems by implicitly mapping the input data into a higher-dimensional feature space using kernel functions ($\varphi(x)$). This transformation helps identify of nonlinear relationships that may not be immidiately apparent in the original space. SVR's goal is to maximize the number of data points within an

epsilon (ε) tolerance margin and then fit an optimal linear regression function to these points. To accomplish this, SVR uses an ε-insensitive loss function. This loss function is insensitive to errors within the ε-margin while penalizing deviations that exceed this margin with penalties (ξ). This feature enhances SVR's robustness to noise and outliers [20].

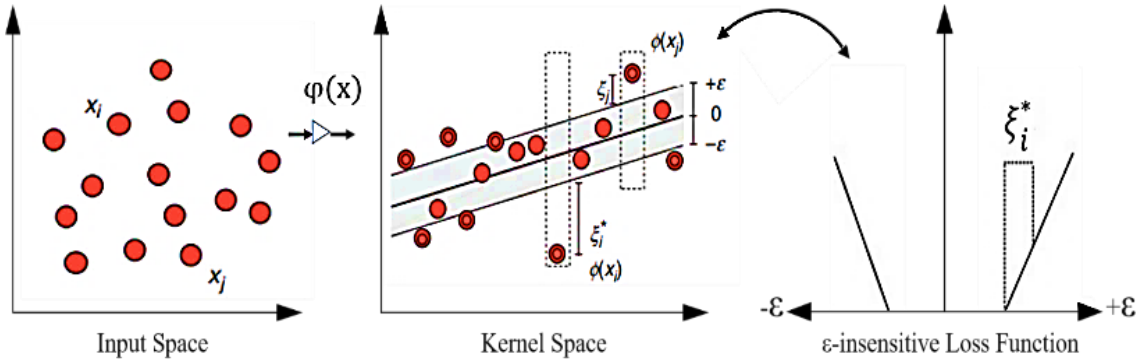

Fig. 2. Schematic representation of the Support Vector Regression (SVR) algorithm.

3. Experimental

3.1. Experimental setup

A gamma-ray spectroscopy system, consisting of a detector, high voltage power supply, pulse shaping amplifier, and multi-channel analyzer, was used for data acquisition. Two experimental setups were employed, utilizing ORTEC HPGe (model GEM-40190) and NaI(Tl) (Amcrys 10 S 10/3. VD(p), PA) detectors. To optimize the detectors performance and achieve the minimum full width at half maximum (FWHM), amplifier settings such as shaping time, coarse gain, fine gain, and pole-zero cancellation were carefully adjusted. Furthermore, the positioning of the sources in front of the detectors was determined in such a manner that the count rate exceeded 1000 counts per second, and the dead time for measuring all samples was kept below 1% (5 seconds). The acquisition time ensured that the statistical error remained below 1.0%. Notably, the HPGe detector exhibited a superior FWHM of 2.3 keV compared to the 74 keV obtained with a NaI(Tl) detector for the 1332 KeV gamma-ray peak of ^{60}Co. In this regard, additional details can be found in Saeidi et al [12].

3.2. Dataset creation

To train the model, a dataset containing spectra from both NaI(Tl) and HPGe detectors was required. This involved measuring the individual spectra of ^{60}Co (1.035 ± 0.02 μCi as of 18 Jan 2012), ^{22}Na (0.795 ± 0.02 μCi as of 18 Jan 2012), ^{152}Eu (1.005 ± 0.03 μCi as of 20 Apr 2013), ^{137}Cs (1.115 ± 0.02 μCi as of 18 Jan 2012), and ^{133}Ba (1.15 ± 0.02 μCi as of 18 Jan 2012), as well as spectra from various combinations of these radioisotopes, using both detectors. The background spectrum was also measured and then subtracted from all spectra in the dataset. To prepare the data for model input, the spectra were first normalized to the integral. Subsequently, the single radioisotope spectra (including 5 samples, as shown in Fig. 3) were used to train the model, while the multiple radioisotope spectra (including 26 samples) were used to evaluate model performance.

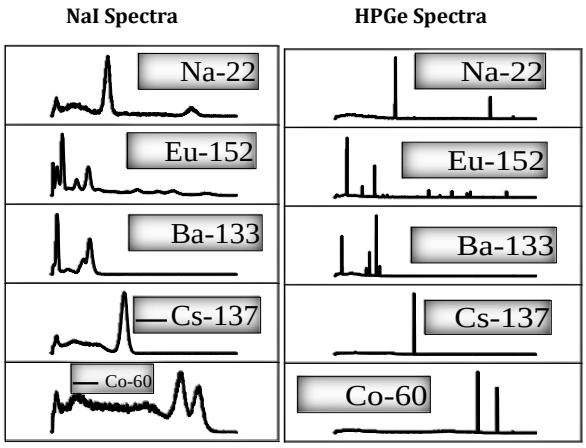

Fig. 3. Representative single spectra of radioisotopes acquired using NaI and HPGe detectors for training data.

4. Results and discussion

This study evaluated the performance of the regression chain model using an experimental test dataset. The dataset comprised gamma-ray spectra acquired from various combinations of radioisotopes measured by a Sodium Iodide detector.

Three types of kernel, specifically linear, polynomial, and radial basis function (RBF) were utilized. The Model's performance was evaluated using the experimental multiple spectra test dataset, and the results are shown in Table 1. R-squared was used as a measure of the model accuracy, and the best value for it is one.

Table 1. Accuracy of MIMOSVR algorithm versus different Approachs.

Approach	Accuracy		
	Polynomial kernel	RBF kernel	Linear kernel
Chained	0.9703	0.9152	0.2719

Fig. 4 exemplifies the input spectra and corresponding model outputs, utilizing various kernel functions, including linear, RBF, and polynomial for several samples within the dataset. Additionally, the equivalent spectra obtained through measurements with the HPGe detector are illustrated for comparison with the resulting output. These samples contained the following radioisotopes: (a) Barium-133 and Cesium-137 (b) Cobalt-60 and Sodium-22, (c) Barium-133, Cesium-137 and Cobalt-60, (d) Europium-152, Cobalt-60, Sodium-22, (e) Barium-133, Cesium-137, Cobalt-60, and Sodium-22, (f) Barium-133, Europium-152, Cesium-137, Cobalt-60, and Sodium-22. The gamma spectrum of Barium-133 displays characteristic energy peaks at 80.9979, 276.3989, 302.8508, 356.0129, and 383.8485 keV, each with a significant branching ratio. While the NaI detector struggles to distinguish these peaks due to limitations in its energy resolution, the HPGe detector can easily differentiate them. The proposed models, which utilize Radial Basis Function (RBF) and polynomial kernels, effectively learned the transformation between the Barium-133 spectra obtained with both detectors, even when combined with other radioisotopes, as shown in Figs. 4a, 4c, and 4f.

Fig. 4b illustrate the performance of the models for the combined spectrum of Cobalt-60 and Sodium-22. The Cobalt-60 spectrum shows characteristic energy peaks at 1173 keV and 1332.5 keV, while Sodium-22 has energy peaks at 511 keV and 1274 keV. In the combined NaI spectrum, the second peak of Sodium-22 significantly overlaps with the Cobalt-60 peaks, making it indistinguishable. Surprisingly, the proposed model, despite never encountering this combined state before, successfully seprated these overlapping peaks in the simulated HPGe spectrum, producing a result that closely resembling the genuine HPGe spectrum.

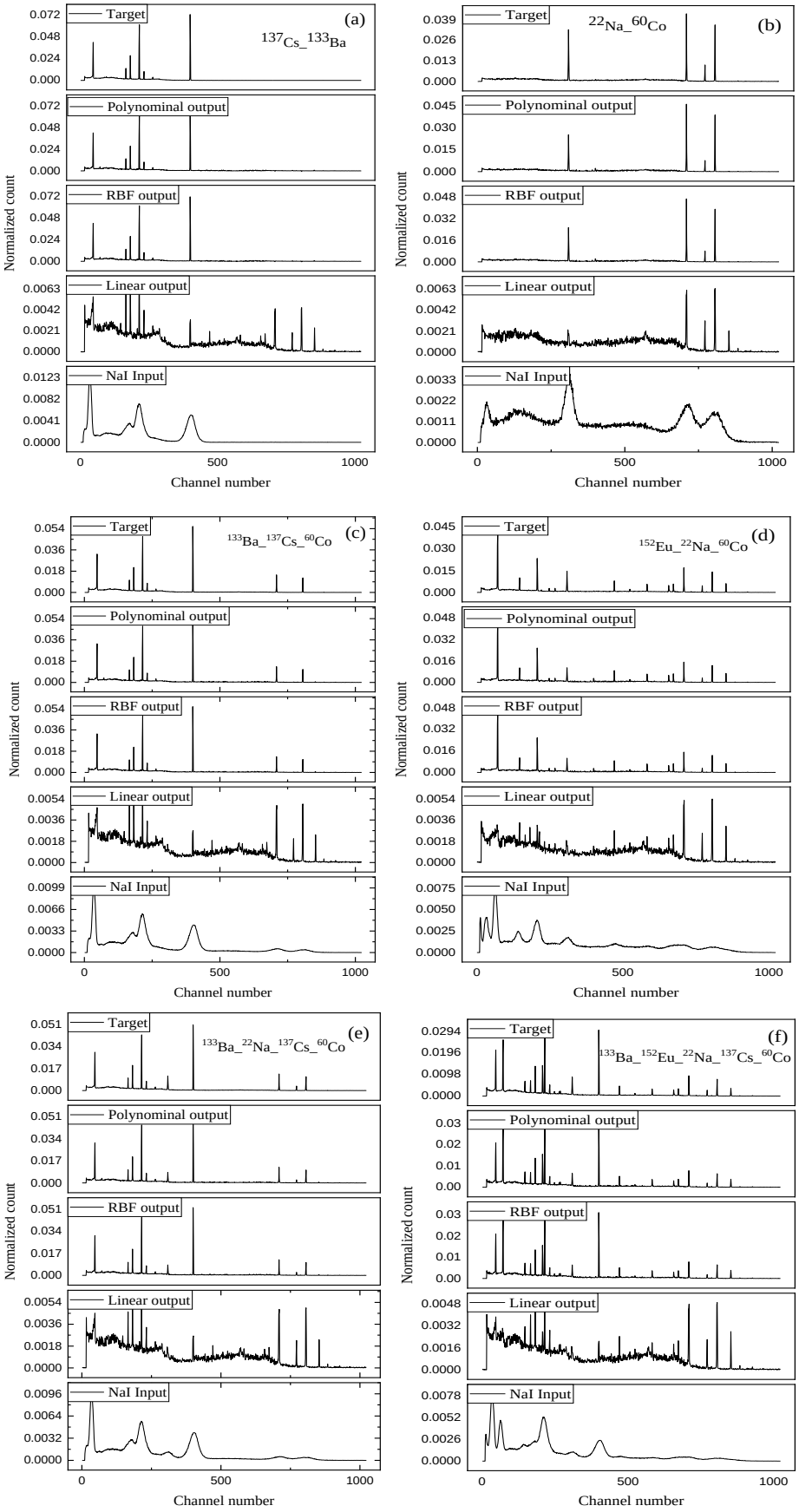

Fig. 4. The input NaI spectra and corresponding model outputs for radioisotopes: (a) ^{133}Ba and ^{137}Cs (b) ^{60}Co and ^{22}Na, (c) ^{133}Ba, ^{137}Cs and ^{60}Co, (d) ^{152}Eu, ^{60}Co, and ^{22}Na, (e) ^{133}Ba, ^{137}Cs, ^{60}Co, and ^{22}Na, (f) ^{133}Ba, ^{152}Eu, ^{137}Cs, ^{60}Co, and ^{22}Na.

Europium-152 has multiple energy peaks that overlap significantly with those of Barium-133 at lower energies and with Cobalt-60 and Sodium-22 at higher energies. Fig. 4d displays the combination of Europium-152 with Cobalt-60 and Sodium-22, while Fig. 4f shows their combination with Barium-133. The complexity of the NaI spectra in these combinations is evident, yet the RBF and polynomial models demonstrate their ability to generate HPGe spectra with well-resolved, distinct energy peaks.

As illustrated in Figs. 4a-f, the proposed SVR-based regression chain model did not perform acceptably for any of the samples with the linear kernel function. The RBF and polynomial kernel functions showed almost identical and excellent performance for constructing the desired HPGe spectrum. They successfully transform the input NaI spectra into the desired HPGe spectra, even for complex combinations of radioisotopes. Notably, the model accomplishes this feat using only the spectra of single radioisotopes, demonstrating significantly greater performance compared to previous methods that require substantially larger datasets (e.g., over 3000 samples for FCNN). Furthermore, the proposed model exhibits a reduction in extra positive peaks and reversed peaks compared to the FCNN model.

The normalized HPGe spectrum obtained contains valuable information that can be used to identify energy peaks associated with an unknown sample, identify radioisotopes, and determine the contribution of each radioisotope in a multi-radioisotope spectrum. However, the current model is not suitable for activation measurements. Future work will focus on calculating actual counts, allowing the spectrum to be used for activity calculations.

5. Conclusions

This paper proposes a novel idea to convert low-resolution NaI spectra to high-resolution HPGe spectra using multi-output regression chain structure based on support vector regression. The model exhibited excellent results using RBF and polynominal kernels, despite limitations with the linear kernel function. The NaI spectra of different combinations of radioisotopes have many energy peaks, which overlapp more than the spectra of single radioisotopes. However, the proposed model, although trained only with the spectra of single radioisotopes (5 training samples), showed excellent performance for a dataset of various combinations of radioisotopes (26 test samples). In future work, the performance of the model can be further investigated for more radioisotopes, and more complex combination states can be created by changing the measurement conditions, optimizing the model for them.

The methodology presented in this work: using NaI detectors for the prediction of HPGe spectra, offers several advantages, including: **1.** Cost-effectiveness: NaI(Tl) detectors are considerably cheaper than HPGe detectors, making them a more accessible option for various applications. **2.** User-friendliness: NaI(Tl) detectors are generally easier to operate and maintain compared to HPGe detectors, requiring less specialized expertise. **3.** Enhanced peak identification and quantification: Improved resolution enables the separation of overlapping peaks, leading to more accurate identification and quantification of individual gamma-ray emitters. **4.** Reduced analysis time: The use of constructed HPGe spectrum can significantly reduce analysis time compared to relying solely on NaI measurements.

Future work will focus on investigating the model's performance with an even wider range of radioisotopes and exploring the creation of more complex combination states by altering measurement conditions and subsequently optimizing the model for these scenarios.

Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work.

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