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Constructing energy spectrum of inorganic scintillator based on plastic scintillator by different kernel functions of SVM learning algorithm and TSC data mapping

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Abstract: In this paper, a novel idea is developed to construct energy spectrum of inorganic scintillator detector (e.g. NaI(Tl)) using energy spectrum of organic scintillator detector (e.g. NE102) by means of a model-free method. For this purpose, support vector machine (SVM) accompanied with different kernel functions (i.e. linear, polynomial, and Gaussian) is applied. The spectra of NE102 and NaI(Tl) detectors of the single radioisotopes (i.e. Co60, Cs137, Na22, and Am241) are utilized for training of SVM. In other words, data of NE102 detector are input spectrums of training patterns and data of NaI(Tl) detector are target spectrums of training patterns. To construct an appropriate mapping function between spectrums of detectors, a kind of cross-correlation technique namely mapping of totality of channels to single channel (TSC) is utilized. In the test process, spectrums of different combinations of the target radioisotopes are constructed and the results are compared with the measured spectrums. Polynomial kernel function gives good results. Linear and Gaussian kernel functions do not give so appropriate results. The major advantages of the developed method are: 1- The NaI(Tl) spectrums of different combinations of the target radioisotopes are constructed only by training of single radioisotopes spectrums. 2- Energy spectrums of high price/ high resolution detectors (i.e. inorganic scintillator detectors) can be constructed using low price/ low resolution detectors (i.e. plastic scintillator detectors). 3- This method can be used to construct energy spectrum of any type of inorganic scintillator (e.g. BGO detector) using either plastic or liquid scintillators. Liquid scintillator detectors (e.g. NE213) are more appropriate for detection/identification of radioactive sources which emit both gamma and neutron radiations. However, these detectors give low resolution gamma spectrums. The developed method can be appropriate for construction of higher resolution gamma spectrums for this type of sources. This application of the developed method is discussed in the manuscript.

Keywords: Pattern recognition, cluster finding, calibration and fitting methods; Particle detectors; Scintillators and scintillating fibres and light guides

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1 Introduction

Four mechanisms including photoelectric absorption, Compton scattering, pair production, and photonuclear reaction are significant interactions of gamma radiation with material [1]. Photoelectric interaction is proportional to Z^4/E^3. Compton mechanism is approximately proportional to the electron density of the target, and pair production is proportional to Z^2+Z reaction. Gamma energy must exceed a certain minimum value for photonuclear. Where, Z is atomic number of attenuating medium and E is energy of gamma ray.

One of the best instruments for spectrometry of gamma radiation is scintillator detector. A scintillator detector converts the interactions of gamma radiation to light pulses and photomultiplier tube (PMT) converts the generated light pulses to electric pulses for detection/identification of radiation. The photocathode of PMT, a focusing electrode, and dynodes (e.g. 10 or more) multiply the number of electrons which strike at each dynode [2]. Inorganic scintillators with high density and high-Z are appropriate choices for gamma-ray spectroscopy while plastic/liquid scintillators (e.g. NE102 and NE213) with low density and low-Z are not so suitable for this purpose. Even though, inorganic scintillators are available with a large variety of forms, constituent materials, and sizes, however, NaI(Tl) crystals are the most widely used for gamma spectroscopy. High light output and very good match to the sensitivity of PMT provide good energy resolution by NaI(Tl).

The motivation of this study is development of a method to construct energy spectrum of inorganic scintillator (e.g. NaI(Tl)) using energy spectrum of organic scintillator (e.g. NE102) by means of supervised learning methods. Up to now, supervised learning methods have been extensively used for prediction, estimation, and regression [3]. In this study, support vector machine (SVM) as a supervised learning method accompanied with different kernel functions is used for construction of energy spectrum of NaI(Tl) detector [4]. SVM acts good in cases when there is no/little information about data structure (i.e. unstructured or semi-structured data). In addition, SVM can escape local minima and overfitting as well as it can balance between training data and test data (i.e. balance between memorization and generalization) [5]. Moreover, SVM in most cases gives better results compared with artificial neural networks (ANN) [6].

Estimation/Regression/construction of data series is usually done using either autocorrelation or cross-correlation techniques [7]. Autocorrelation technique estimates current/future value of data series by past/current value of that data. Cross-correlation technique maps input patterns to the targets. In figure 1, a schematic view of autocorrelation finding/cross-correlation detection by SVM learning algorithm is illustrated. In this study, for construction of energy spectrums of NaI(Tl) detector, the energy spectrums of organic detector are utilized. Therefore, autocorrelation finding cannot be used and cross-correlation detection is more appropriate for spectrum construction.

Outline of the remainder of the present work is as follows. In section 2. SVM learning algorithm is studied. In section 3, a kind of cross-correlation technique which maps spectrum of organic scintillator to spectrum of NaI(Tl) by means of SVM is utilized. In section 4, NaI(Tl) spectrums of the different combinations of the radioisotopes are constructed and the results are discussed. Section 5 attends the conclusion.

2 Support vector machine

In this section a brief review of SVM learning algorithm is given. The more detailed descriptions can be found in the references. SVM is a supervised learning algorithm used for classification, regression, and outlier detection of the target data [8, 9]. SVM utilizes a function either linear or nonlinear to convert multi- classes into multi binary classes. Nonlinear function (i.e. kernel function) maps patterns to higher dimensional space and then a separating hyperplane classifies patterns. In other words, instead of forming a boundary in the original space, where the two classes are not separable, a new higher dimensional space, where the samples are projected by means of kernel function is defined. The back-projection of the separating boundary from this new feature space to the original space will then result in a non-linear boundary for given data [10]. A schematic view of SVM classifier is presented in figure 2. Linear and nonlinear SVM are presented in eq. (2.1) and eq. (2.2), respectively.

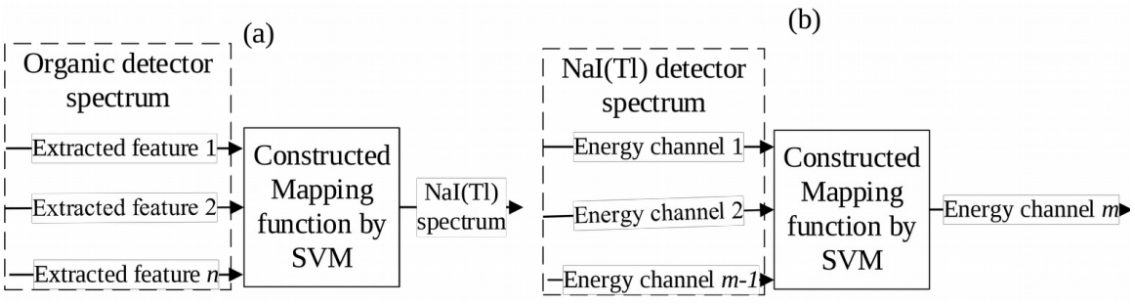

Figure 1. A schematic view of (a) cross-correlation detection (b) autocorrelation finding utilized for construction of NaI(Tl) spectrum using either organic scintillator spectrum or NaI(Tl) spectrum.

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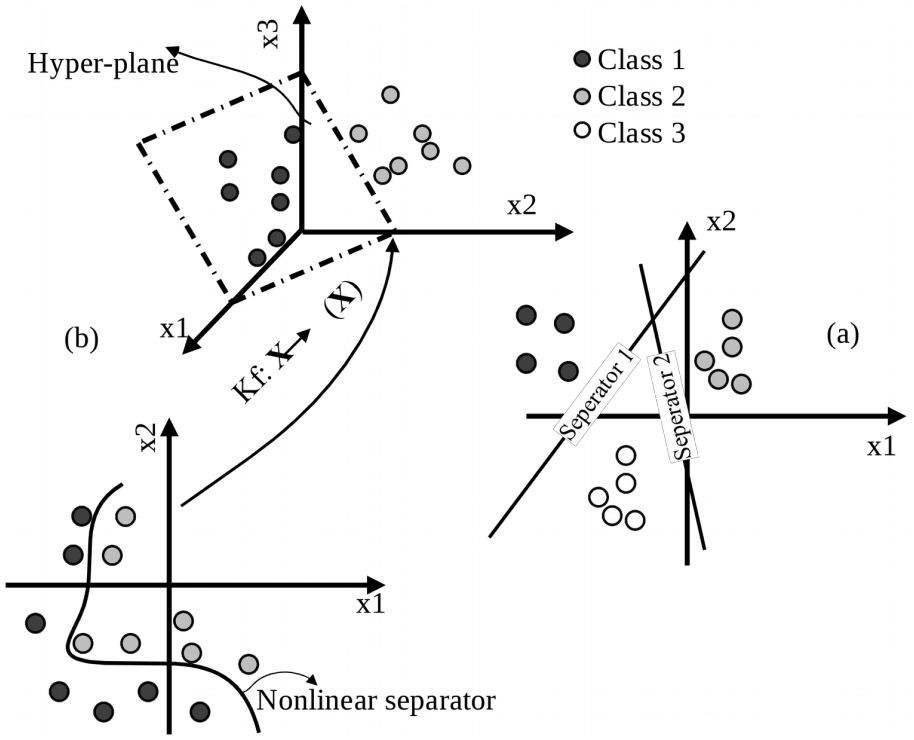

Figure 2. A schematic view of SVM for (a) classification of multi-classes to multi binary classes. (b) nonlinear separating.

$$\text{minimize}: \qquad f(o_{p_1^*}, o_{p_1^*}, \ldots, o_{p_n^*}, \mathbf{w}, c) = \frac{1}{2}|\mathbf{w}|^2 \tag{2.1}$$

$$\text{Subject to}: \qquad \forall_{i=1}^{m}: \ \{t_i \in \{-1, +1\}\}\,(\mathbf{w}.\mathbf{X} + c) \geq 1$$

$$\text{minimize}: \qquad f(o_{p_1^*}, o_{p_1^*}, \ldots, o_{p_n^*}, \mathbf{w}, c) = \frac{1}{2}|\mathbf{w}|^2 \tag{2.2}$$

$$\text{Subject to}: \qquad \forall_{i=1}^{m}: t_i(\mathbf{w}.\mathrm{Kf}(\mathbf{X}) + c) \geq 1$$

Where, o_{p*} is output of unlabeled inputs, $\boldsymbol{w}$ is a weight vector that is normal to the hyperplane, $\boldsymbol{X}$ is vector of inputs, t is target value of each class, c is an offset, m is number of classes, and n is number of inputs. Kf is kernel function.

Different types of Kernel function can be utilized. Linear, polynomial, Gaussian, hyperbolic tangent, sigmoid, and Bessel are conventional forms of kernel functions. Gaussian kernel is used when there is no prior knowledge about the data. In this study the general purpose kernel function (i.e. Gaussian) with linear and polynomial kernel functions are employed. These kernel functions are given by eq. (2.3). Kernel scale for Gaussian function is determined using standard deviation of input data, automatically.

$$\mathrm{K}(x_1, x_2) = \begin{cases} \exp\left(-\gamma \|x_1 - x_2\|^2\right) \text{Gaussian kernel functioin; Kernel scale} = \frac{1}{\gamma^2} \\ x_1' x_2 \text{Linear Kernel function} \\ \left(1 + x_1' x_2\right)^p \text{Polynomial Kernel function; p = Polynomial order} \end{cases} \tag{2.3}$$

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There is a minor difference between regression and classification by SVM [11]. In the regression by SVM, a model is formed between input data and targets. As an example, eq. (2.4) gives a linear model. Where, y is target. This model is similar to a linear boundary which is utilized by SVM for classification. Therefore, regression by SVM is converted to SVM classification.

$$y = wx + c \tag{2.4}$$

3 Construction of mapping function between spectrums of organic and NaI(Tl) detectors by means of SVM and TSC data mapping

There are no extracted features for spectrum of organic detector (e.g. NE102 detector). Therefore, the cross-correlation detection technique presented in figure 1 cannot be applied for construction of mapping function between spectrums of detectors. Moreover, mapping of any energy channel of NE102 detector to similar channels of NaI(Tl) detector is not appropriate. Mapping of single channel to single channel (SCSC) will cause degradation of balance between memorization and generalization of SVM. As an example, NaI(Tl) spectrum of Co-60 with SCSC technique is learned. Figure 3 shows very good agreement of the constructed spectrum of Co-60 in comparison with experimental spectrum (i.e. very good memorization in training process). However, in test process, constructed spectrum of Cs137 which is presented in figure 4 is spectrum of Co60. In other words, the constructed mapping function has no generalization. For construction of an appropriate mapping function between spectrums of NE102 and NaI(Tl) detectors a kind of cross-correlation technique is utilized which creates a correlation between all energy channels of NE102 and any energy channel of NaI(Tl). Totality of channels to single channel (TSC) mapping

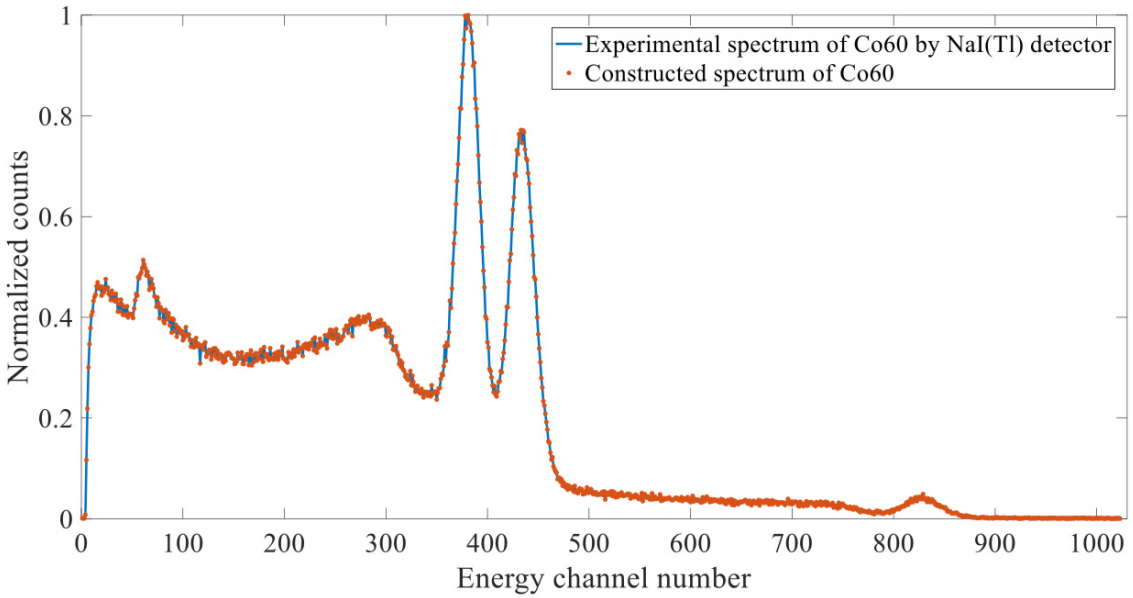

Figure 3. The constructed NaI(Tl) spectrum of Co60 by means of SCSC technique in comparison with the experimental spectrum is illustrated in figure 5. Where, OD_i and ID_i are i-th energy channel of organic detector and inorganic detector, respectively.

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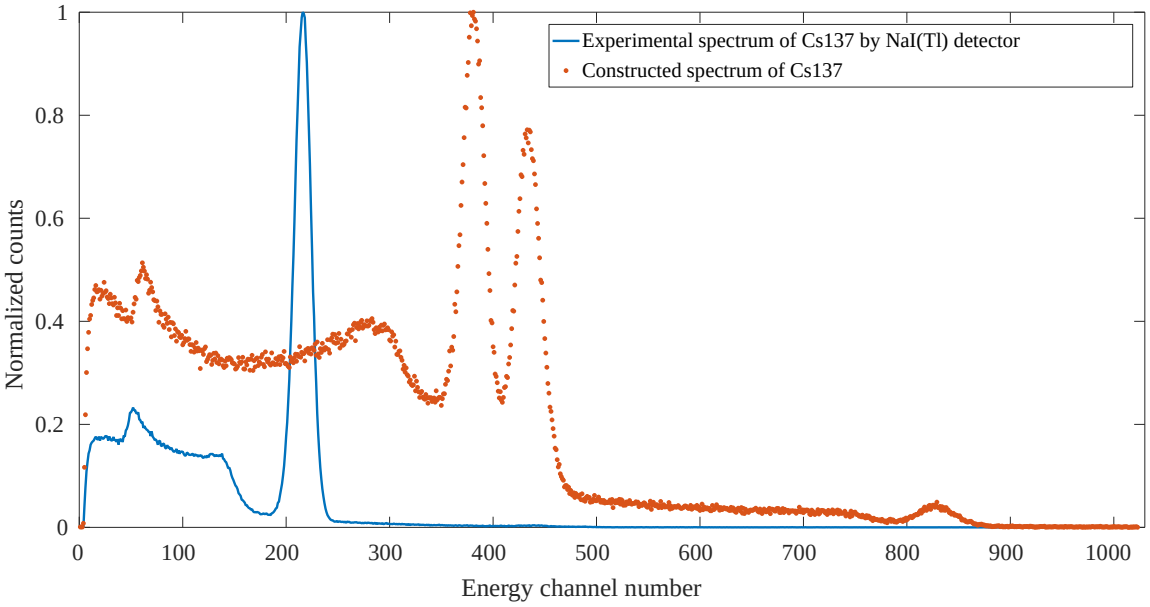

Figure 4. The constructed NaI(Tl) spectrum of Cs137 by means of SCSC technique in comparison with the experimental spectrum.

4 Construction of NaI(Tl) spectrums of different combinations of the radioisotopes

In this section, the TSC technique accompanied with SVM learning algorithm is applied for construction of NaI (Tl) spectrums of different combinations of the target radioisotopes using NE102 spectrums. Moreover, construction of higher resolution gamma spectrum by the developed method for radioactive sources which emit both gamma and neutron radiations is discussed.

Different kernel functions of SVM (i.e. linear, polynomial, and Gaussian) are employed. Training of SVM is done using spectrums of the single target radioisotopes. The training patterns and the test patterns are presented in table 1. As seen form table 1, ratio of the training patterns to all of the patterns is 4/15. This means, according to eq. (4.1), for m target radioisotopes, ratio of training patterns to all of patterns is $m/(2^m - 1)$. Where, $\binom{m}{i}$ represents the different combinations of i number of radioisotopes from m number of radioisotopes. Therefore, 0.267 of the patterns are for training and 0.733 of the patterns are for test. It is important to mention, for training of supervised learning algorithms, conventionally, ratio of training patterns to all patterns is 0.7. In other words, the developed method utilizes smaller fraction of patterns for training and this may increase the chance of method for better generalization.

Training spectrums (i.e. experimental spectrums of the targets radioisotopes) are presented in figure 6. Results of construction of the target spectrums of the training patterns using different kernel functions of SVM are presented in figure 7 up to figure 9. In comparison with experimental spectrums, polynomial kernel function gives more accurate results. Linear and Gaussian kernel functions do not give so appropriate results. Therefore, polynomial kernel function is utilized for construction of the target spectrums of the test patterns. The results show that the developed method is able to distinguish and to learn very similar spectrums (e.g. NE102 spectrums of Na22

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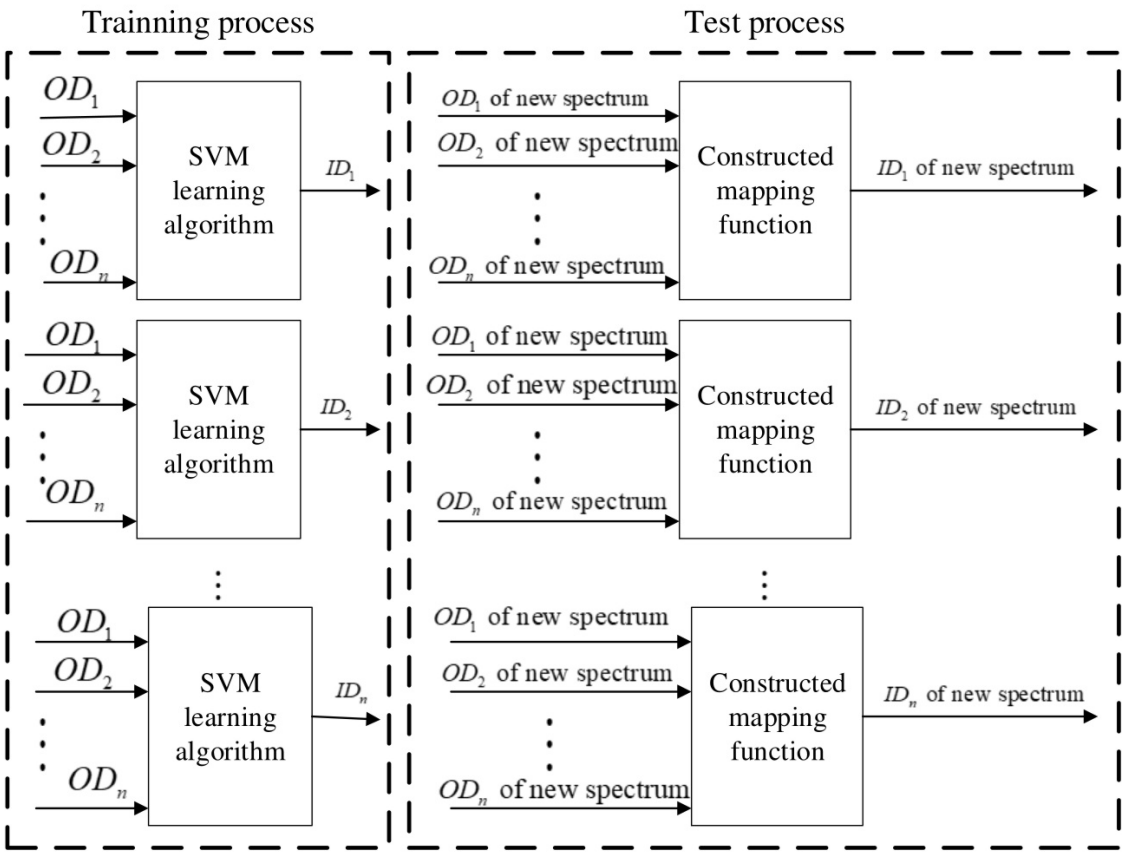

Figure 5. A schematic view of TSC technique.

and Cs137). The spectrometry settings of this study are given in table 2.

$$\begin{aligned}
\binom{m}{1} + \binom{m}{2} + \binom{m}{3} + \ldots + \binom{m}{i} + \ldots + \binom{m}{m} &= 2^m - 1 \text{ all of patterns} \\
\binom{m}{1} &= m \text{ training patterns} \\
\binom{m}{2} + \binom{m}{3} + \ldots + \binom{m}{i} + \ldots + \binom{m}{m} &= 2^m - (m+1) \text{ test patterns}
\end{aligned} \tag{4.1}$$

The constructed NaI(Tl) spectrums for the input spectrums of the test patterns by polynomial kernel function of SVM are given in figure 10 up to figure 14. Results show that, in some cases, photo-peaks of the constructed spectrum are relocated in comparison with the experimental spectrum. Displacement of photo-peaks can be occurred as a function of different settings of spectrometry instruments. For example, different settings of amplifier (i.e. fine gain, coarse gain, shaping time, etc.) have effect on the position of photo-peaks. This issue is illustrated in figure 15. Therefore, the constructed spectrum is appropriate even if its photo-peaks are not exactly identical with the experimental ones. In other words, the shape of the constructed spectrum is more important

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Table 1. Training patterns and test patterns.

Training patterns		Test patterns	
Inputs (spectrums of NE102)	Targets (spectrums of NaI(Tl))	Inputs (new spectrums of NE102)	Targets (new spectrums of NaI(Tl))
Co60	Co60	Co60, Cs137	Co60, Cs137
Cs137	Cs137	Co60, Na22	Co60, Na22
Na22	Na22	Co60, Am241	Co60, Am241
Am241	Am241	Cs137, Na22	Cs137, Na22
		Cs137, Am241	Cs137, Am241
		Na22, Am241	Na22, Am241
		Co60, Cs137, Na22	Co60, Cs137, Na22
		Co60, Cs137, Am241	Co60, Cs137, Am241
		Co60, Na22, Am241	Co60, Na22, Am241
		Cs137, Na22, Am241	Cs137, Na22, Am241
		Co60, Cs37, Na-22, Am241	Co60, Cs37, Na-22, Am241

Table 2. The spectrometry settings of the current study.

Detector	Size	High voltage	Amplifier gain		Shaping time(μs)	Live time(μs)	Distance to detector
			Fine	Coarse			
NaI(Tl)	3 inches	700	0.7	30	3	180	0 cm
NE102	3 inches	-1900	0.7	30	1	180	0 cm

for identification of the radioisotopes. Therefore, the developed method is more appropriate for generation of NaI(Tl) spectrum and is not so useful for exact construction of experimental spectrum (ECES). One of the techniques for ECES is training of supervised learning method by generated pulses of detectors. Pulses have features (i.e. rise time, fall time, shaping time, amplitude, etc.) which are more suitable for cross-correlation detection. This method is under development and will be reported as the subsequent results.

To examine the sensitivity of the developed method to the different settings of spectrometry, the NE102 spectrum of Co60 is given by new setting. This setting and the constructed NaI(Tl) spectrum are given in table 3 and figure 16, respectively. The results show that the new setting does not have significant side-effect on the accuracy of the constructed spectrum.

Construction of higher resolution gamma spectrum for radioactive sources which emit both gamma and neutron radiations can be an application of the developed method. These sources are more detectable/identifiable using liquid scintillator detectors (e.g. NE213). In other words, high concentration of hydrogen of liquid scintillator detectors increases macroscopic cross section of elastic scattering of this type of detectors and makes possible detection/identification of fast neutrons in addition to gamma ray. However, NE213 gives low resolution spectrum for gamma radiation. The

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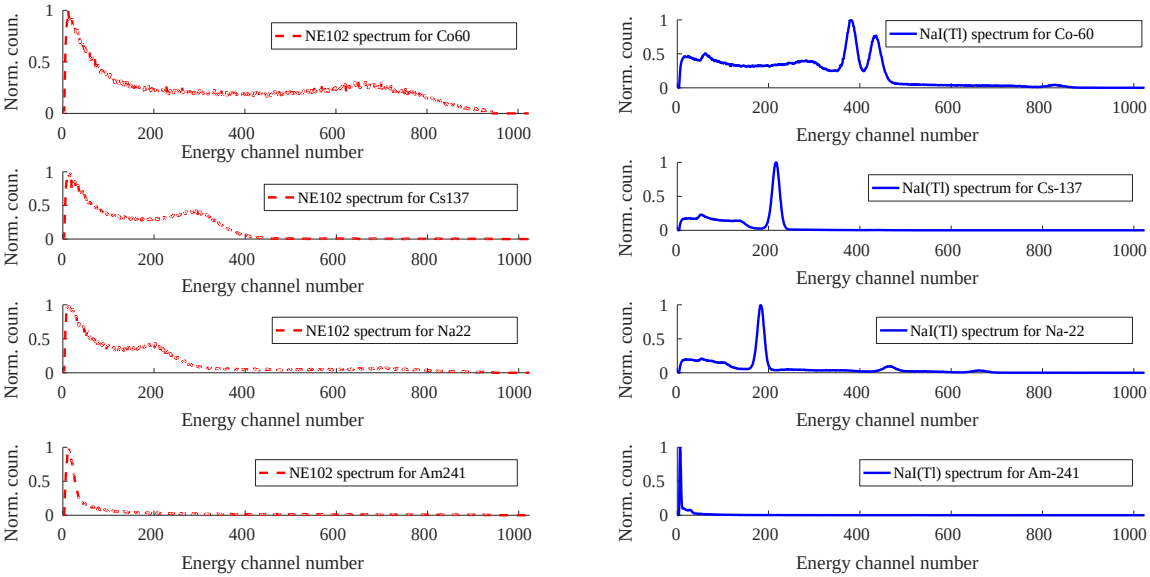

Figure 6. The training spectrums.

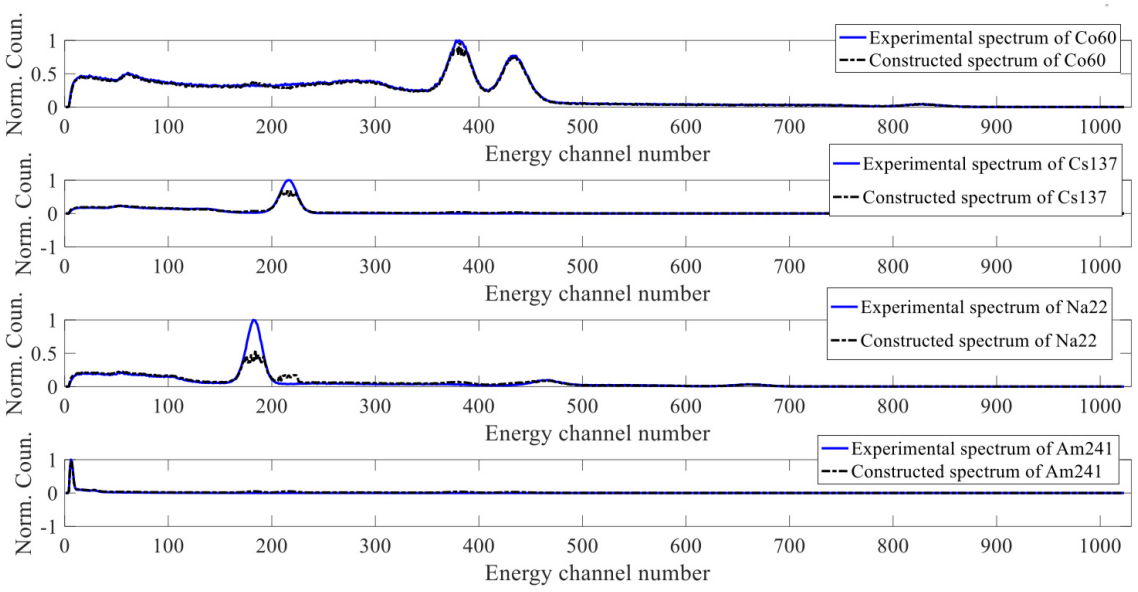

Figure 7. The constructed spectrums by linear kernel function of SVM and TSC technique for the input spectrums of training patterns in comparison with the experimental spectrums.

developed method may be utilized to construct higher resolution spectrum for gamma radiation. First of all, gamma/neutron interactions with detector (i.e. neutron/gamma pulses) must be separated. Pulse shape discrimination (PSD) based on constant fraction discriminator (CFD) is one of the techniques used for separation of neutrons/gammas. A schematic view of equipments arrangement for separation of neutron/gamma radiations is given in figure 17 [12]. Time to amplitude convertor (TAC), analogue to digital convertor (ADC), and multi-parameter analyzer (MPA) are specified in figure 17.

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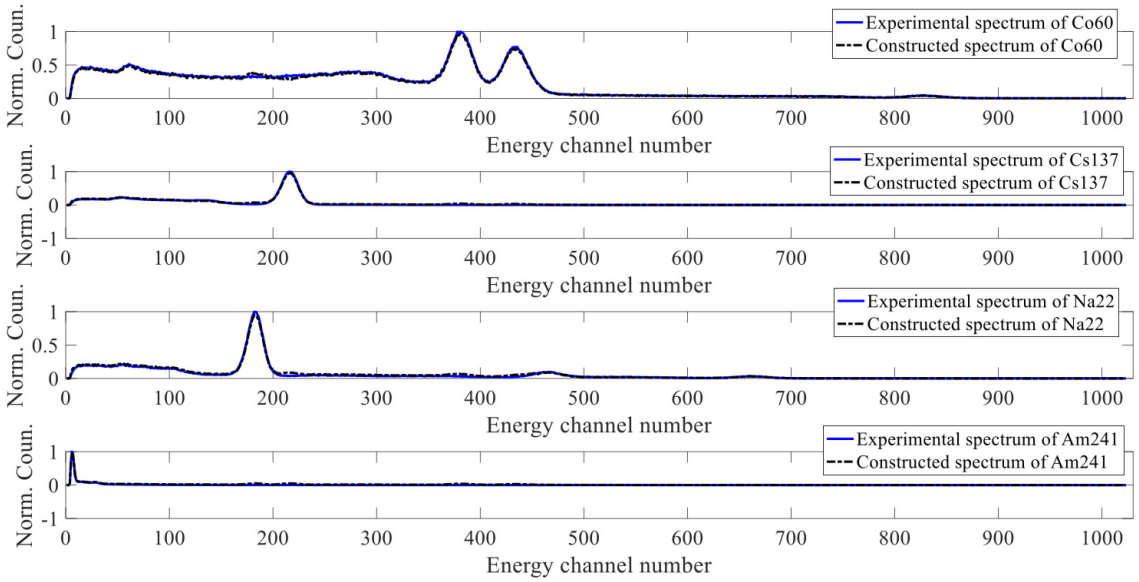

Figure 8. The constructed spectrums by polynomial kernel function of SVM and TSC technique for the input spectrums of training patterns in comparison with the experimental spectrums

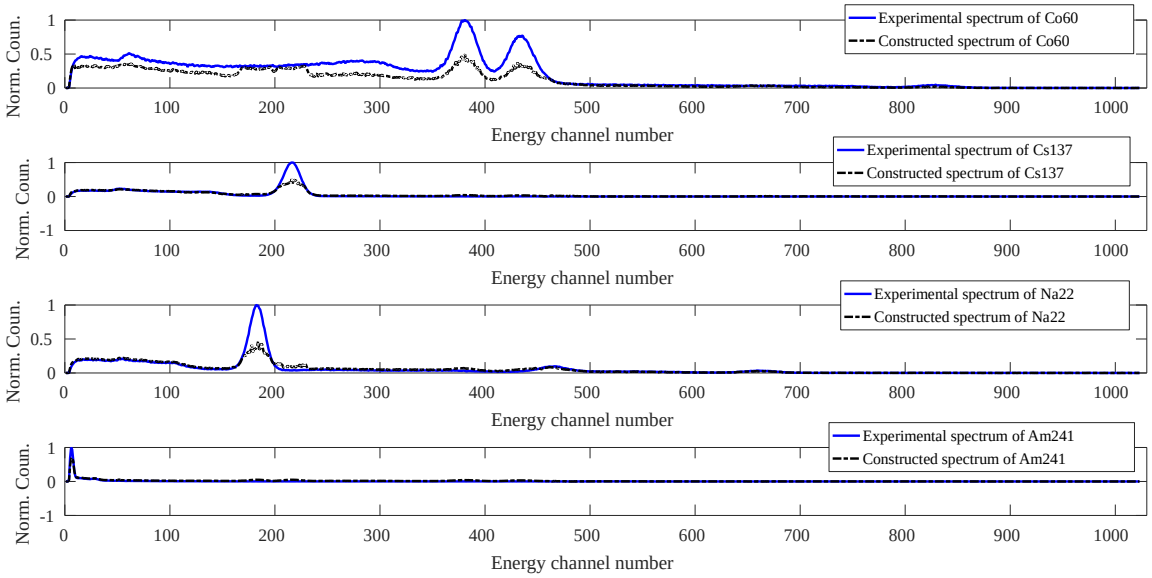

Figure 9. The constructed spectrums by Gaussian kernel function of SVM and TSC technique for the input spectrums of training patterns in comparison with the experimental spectrums.

The gamma spectrum of Am241-Be (i.e. the source with neutron and gamma radiations) by NE213 is presented in figure 18. The constructed spectrum by the developed method for Am241-Be is illustrated in figure 19. Calibration of NaI(Tl) detector indicates that the photo-peaks region of the constructed spectrum (i.e. the highlighted region in the figure 19) show good agreement with the experimental photo-peaks of Am241-Be (i.e. 3.5 MeV up to 4.4 MeV) [13].

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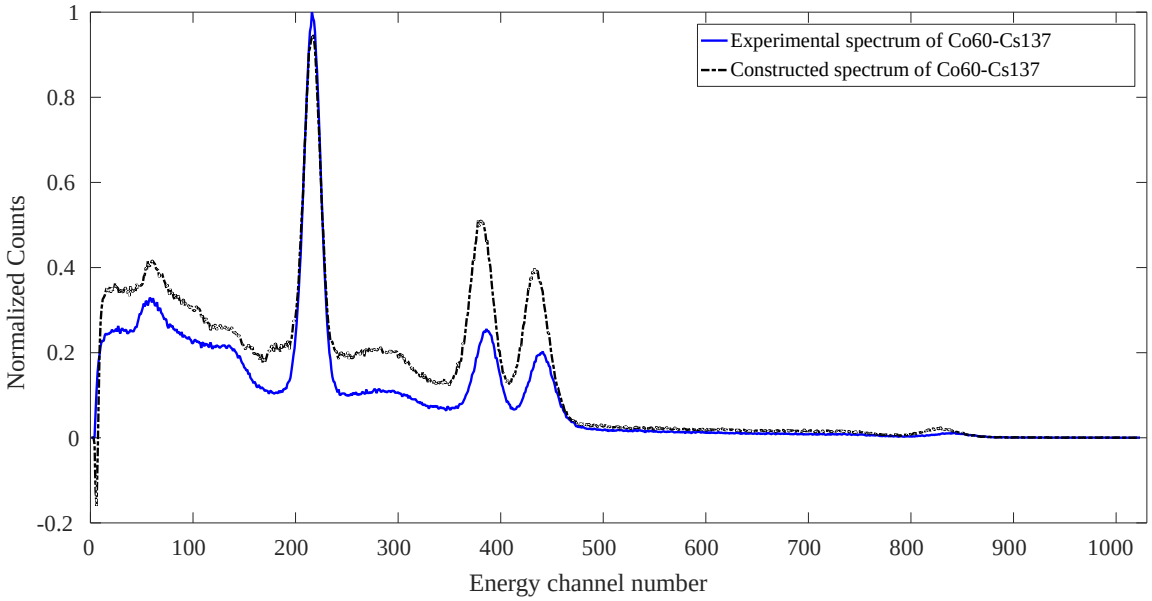

Figure 10. The constructed spectrum by polynomial kernel function of SVM and TSC technique for the Co60-Cs137 in comparison with the experimental spectrum.

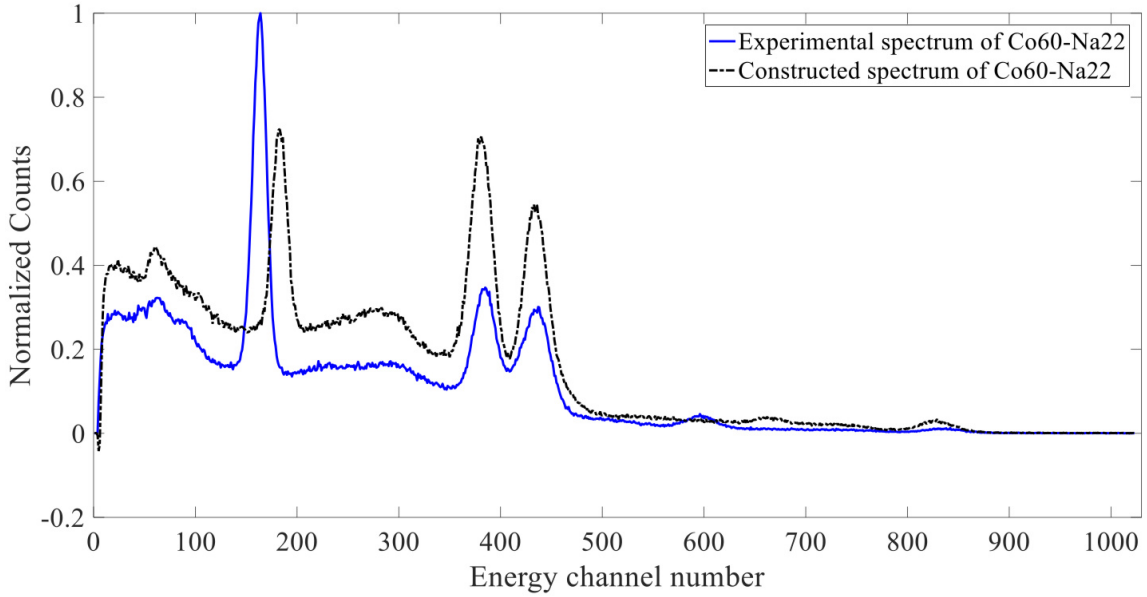

Figure 11. The constructed spectrum by polynomial kernel function of SVM and TSC technique for the Co60-Na22 in comparison with the experimental spectrum.

The major advantages of the developed method are: 1- Construction of NaI(Tl) spectrums of $2^m - 1$ combinations of m radioisotopes are possible only by training of spectrums of single radioisotopes. In this study only 0.267 of data are used for training while seventy to eighty percent of data were used conventionally for training of supervised learning algorithms. 2- The developed method converts the low price/low resolution detectors to high price/ high resolution detectors

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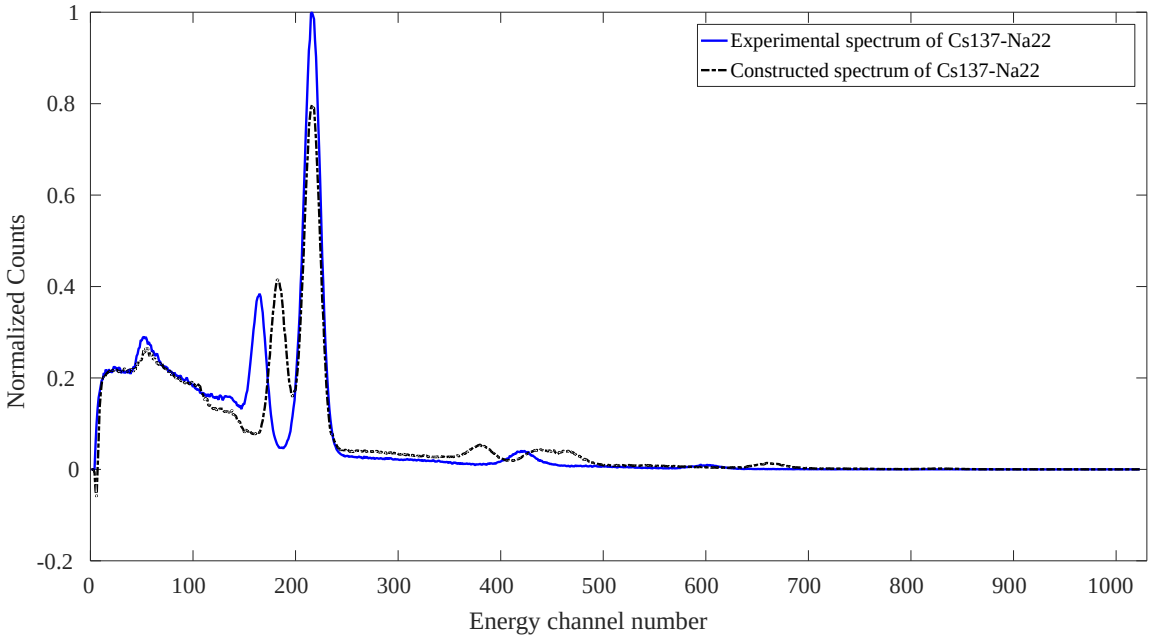

Figure 12. The constructed spectrum by polynomial kernel function of SVM and TSC technique for the Cs137-Na22 in comparison with the experimental spectrum.

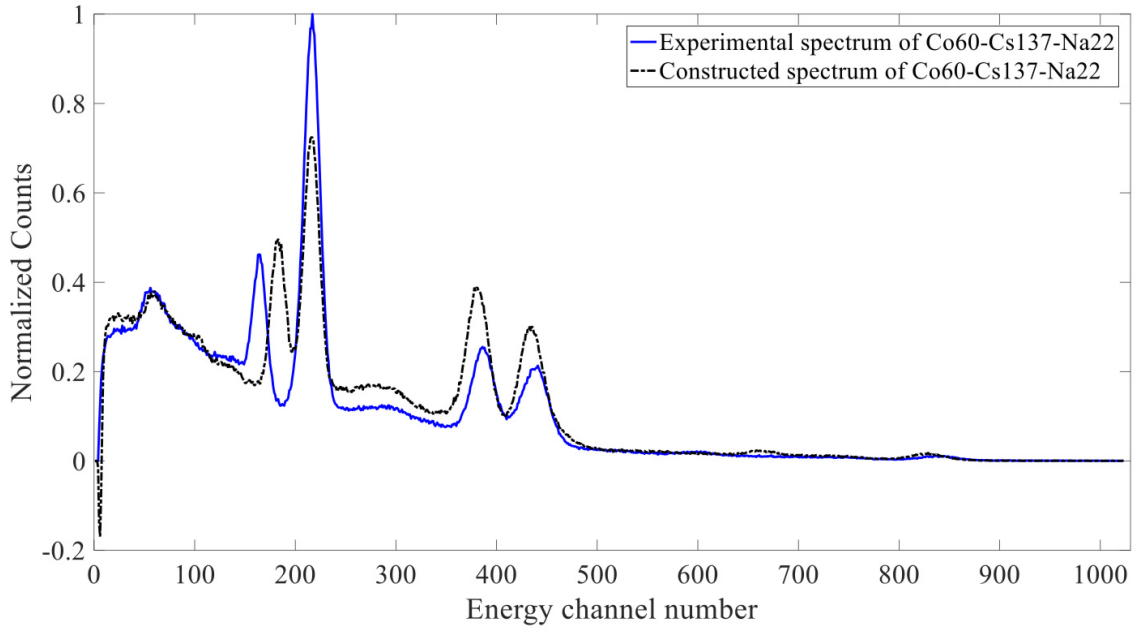

Figure 13. The constructed spectrum by polynomial kernel function of SVM and TSC technique for the Co60-Cs137-Na22 in comparison with the experimental spectrum.

making possible more quality experiments for laboratories/persons which have limited financial resources. 3- This method can be employed for spectrum construction of any type of inorganic scintillator (e.g. BGO scintillator) using either plastic or liquid scintillators.

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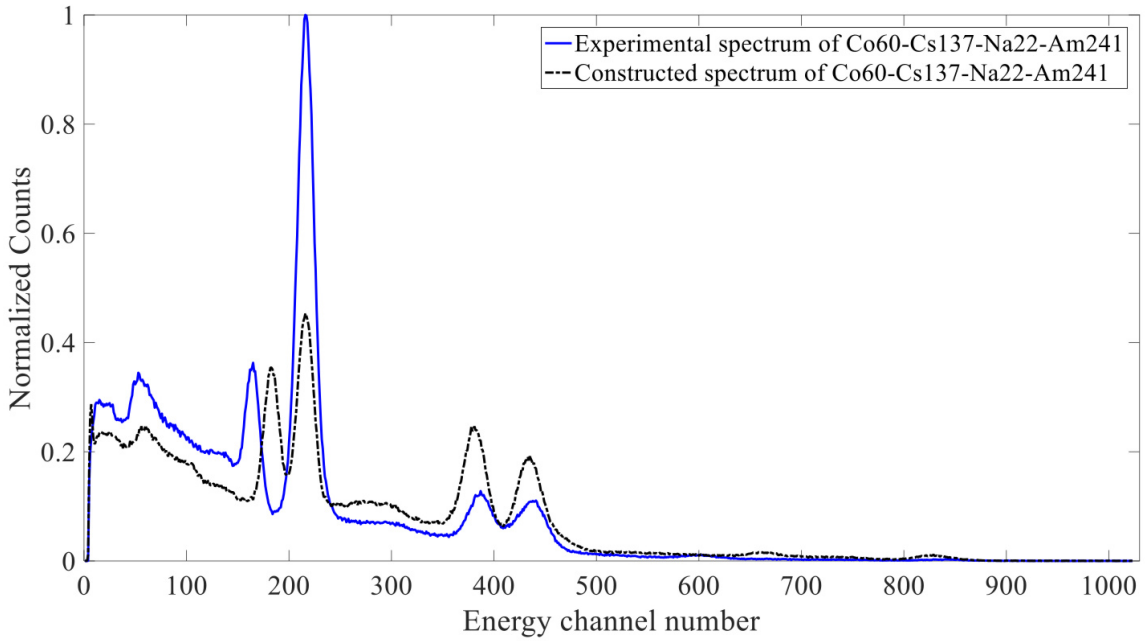

Figure 14. The constructed spectrum by polynomial kernel function of SVM and TSC technique for the Co60-Cs137-Na22-Am241 in comparison with the experimental spectrum.

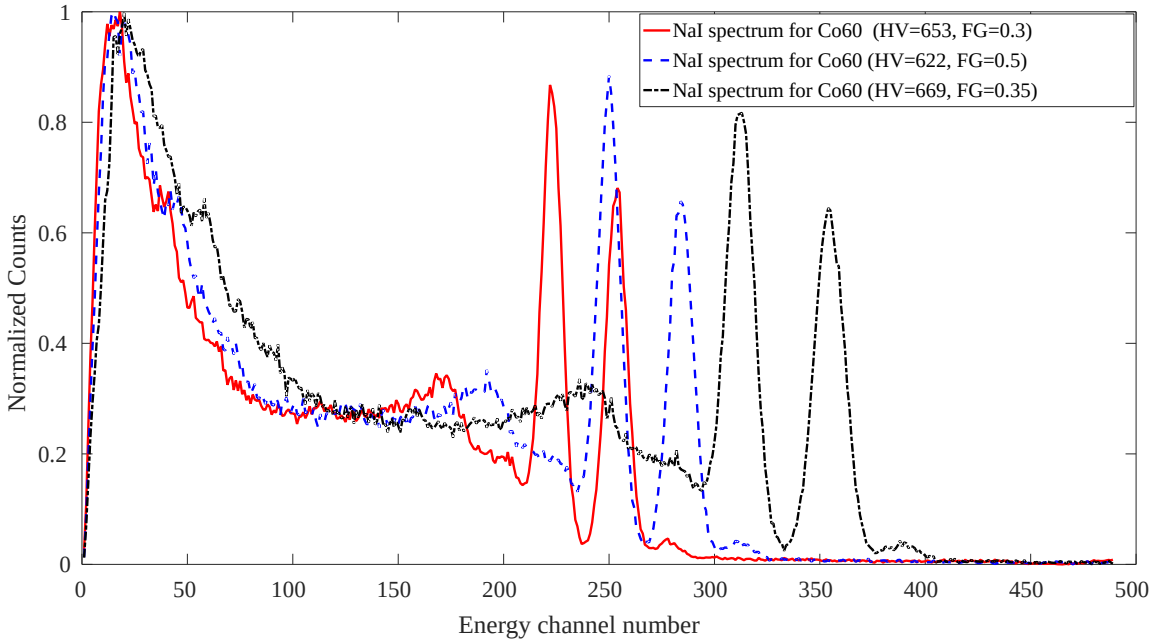

Figure 15. Displacement of Co60 photo-peaks as a function of different settings of amplifier.

It is important to mention, even though the Monte Carlo codes (such as MCNP, Geant, etc.) can be used to construct spectrum of scintillator detectors [14], however, the Monte Carlo codes have some disadvantages: 1- These codes are very time consuming and cannot be utilized for real-time spectrometry in laboratories or in industrial applications while the proposed method constructs

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Table 3. A new setting and training setting of NE102 detector.

Detector		Size	High voltage	Amplifier gain		Shaping time(μs)	Live time(μs)	Distance to detector
				Fine	Coarse			
NE102	Training setting	3 inches	-1900	0.7	30	1	180	0 cm
	New setting	2 inches	-2020	0.3	100	0.25	720	2.5 cm

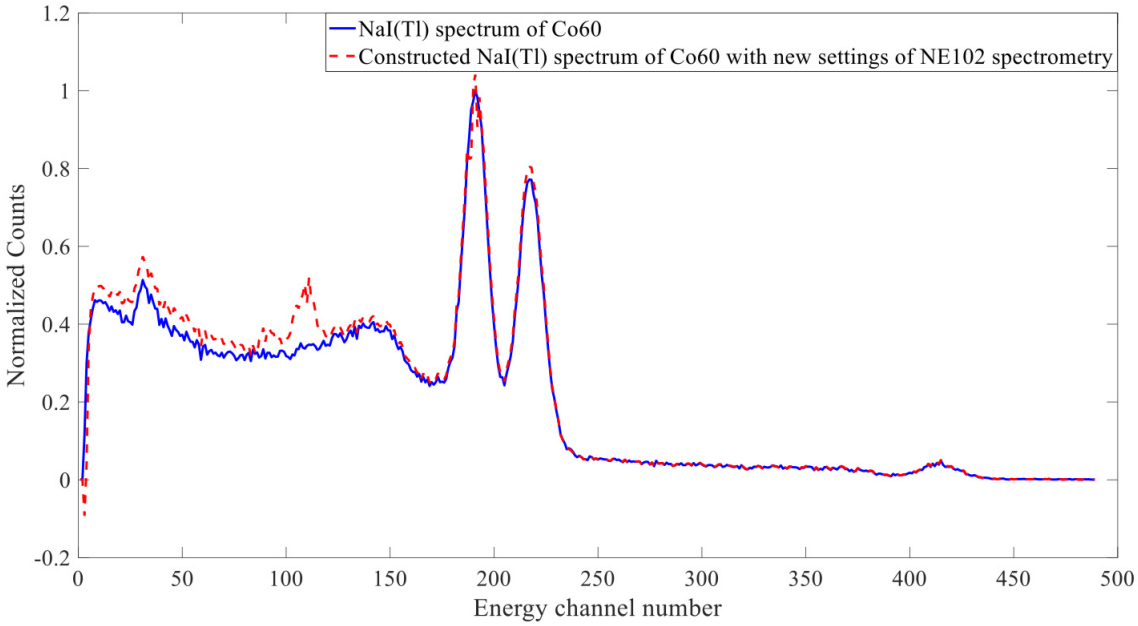

Figure 16. Sensitivity of the developed method to the new settings of NE102 spectrometry.

spectrums immediately. 2- Monte Carlo codes need the trained person to model the target detector while the developed method converts automatically the plastic detector spectrums to the inorganic detector spectrum. 3- Monte Carlo code gives simulated data which may not reflect the complete features of real data while the proposed method is based on the experimental data which is more valuable from the scientific view point. 4- Monte Carlo codes probably needs new modelling with new spectrometry settings (e.g. size of scintillator, electronic settings, distance to detector, etc.) while the proposed method gives acceptable results against new settings.

5 Conclusion

In this paper, a novel idea is developed to construct spectrum of inorganic scintillator detector (e.g. NaI(Tl)) using organic scintillator (e.g. NE102 detector) by means of SVM learning algorithm and TSC technique. Different kernel functions (i.e. linear, polynomial, Gaussian) of SVM are employed

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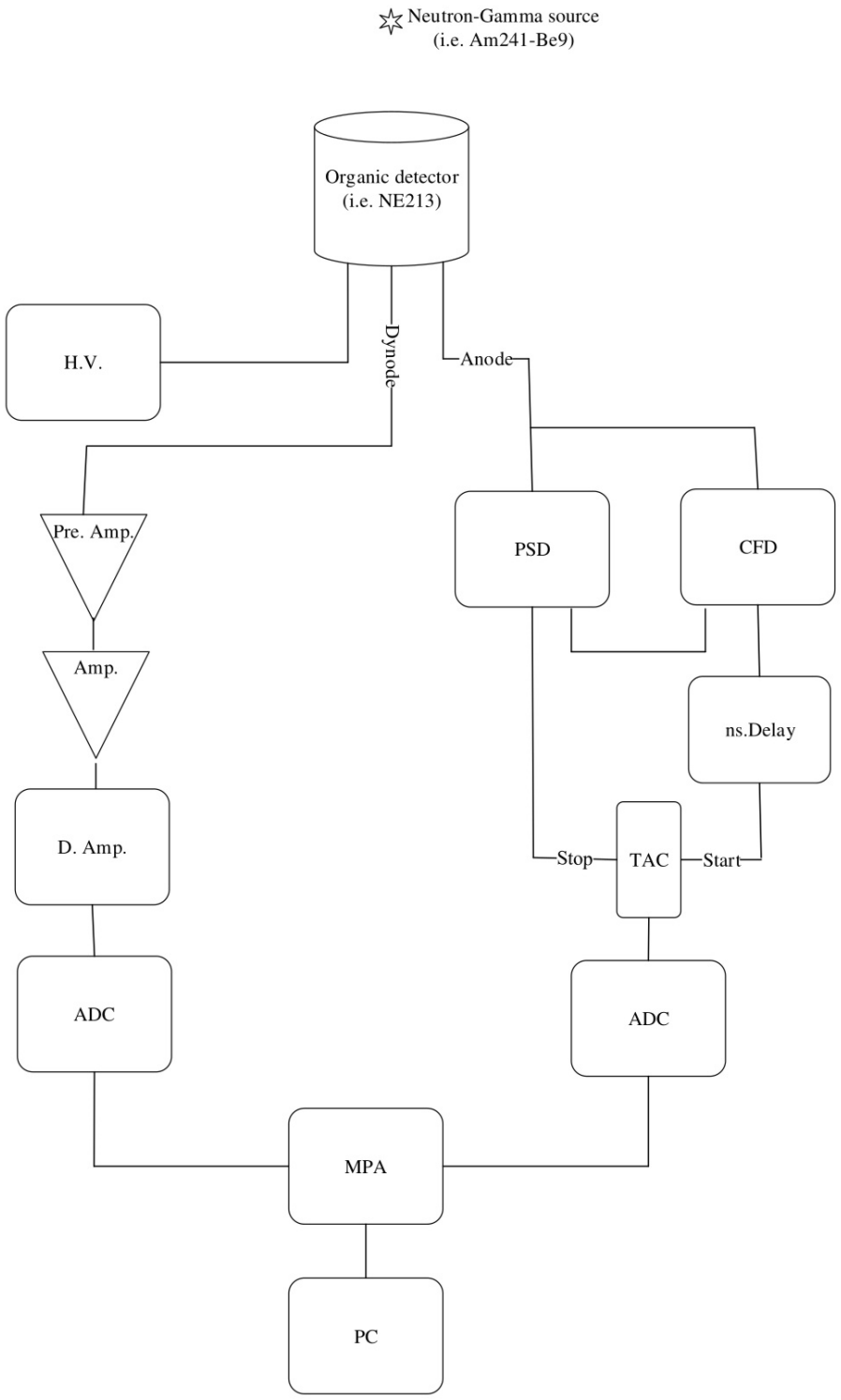

Figure 17. A schematic view of equipments arrangement for separation of neutron/gamma radiations using NE213 detector.

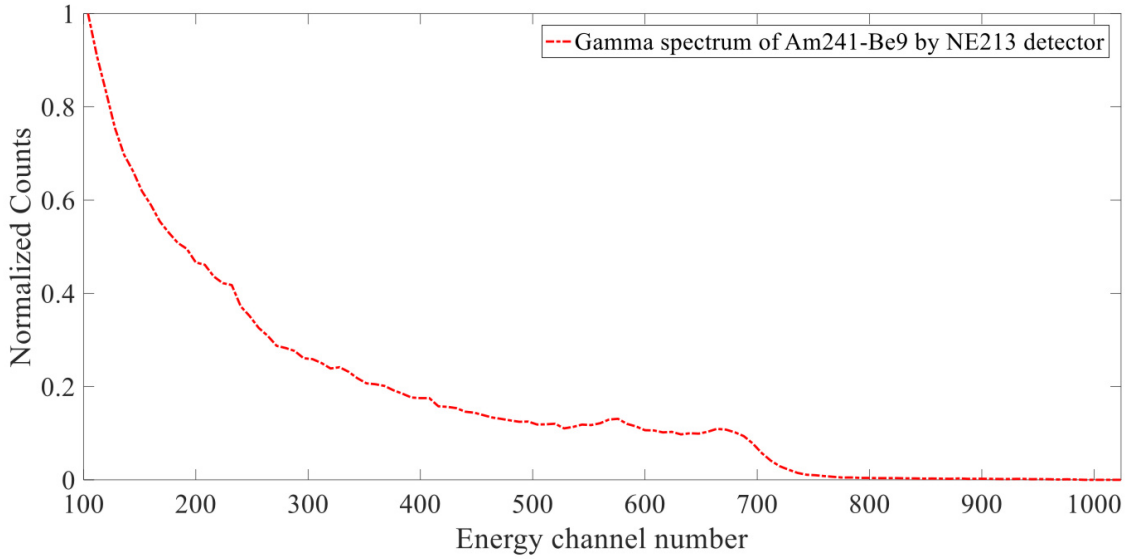

Figure 18. The gamma spectrum of Am241-Be by NE213.

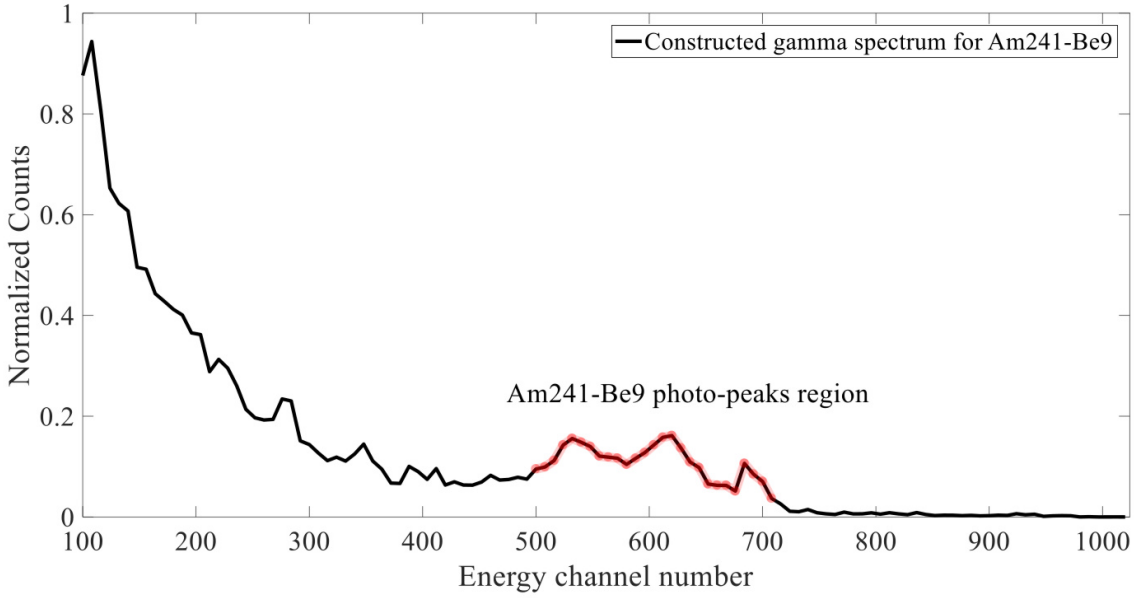

Figure 19. The constructed gamma spectrum for Am241-Be by the developed method.

to show the more appropriate one for spectrum construction. NE102 and NaI(Tl) spectrums of single radioisotopes (i.e. Co60, Cs137, Na22, and Am241) are utilized for training of SVM. In the test process, NaI(Tl) spectrums of different combinations of the target radioisotopes are constructed and the results are compared with the measured spectrums. Results show good agreement of polynomial kernel function. Linear and Gaussian kernel functions do not give so appropriate results. The major advantages of the developed method are: 1- Construction of NaI(Tl) spectrums of $2^m - 1$ combinations of m radioisotopes are possible only by training of spectrums of single

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radioisotopes. 2- The developed method converts the low price/low resolution detectors to high price/ high resolution detectors making possible more quality experiments for laboratories/persons which have limited financial resources. 3- This method can be employed for spectrum construction of any type of inorganic scintillator (e.g. BGO scintillator) using either plastic or liquid scintillators.

Construction of higher resolution gamma spectrum for radioactive sources which emit both gamma and neutron radiations is one of the applications of the developed method. These type of sources are more detectable/identifiable using liquid scintillator detectors (e.g. NE213). However, these detectors give low resolution gamma spectrums. The results show that the constructed spectrum is in good agreement with the experimental spectrum by NaI(Tl).

It is important to mention the developed method is more appropriate for generation of NaI(Tl) spectrum and is not so useful for ECES. One of the techniques for ECES is training of supervised learning method by generated pulses of detectors. Pulses have features (i.e. rise time, fall time, shaping time, amplitude, etc.) which are more suitable for cross-correlation detection. This method is under development and will be reported as the subsequent results.

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