Optimized Spectral Transformation for Detection and Classification of Buried Radioactive Waste - 11310

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ABSTRACT

We investigate detection and classification of buried radioactive materials of interest using data collected by a Sodium Iodide (NaI) detector with short sensor dwell time (i.e., less than or equal to 1s). The objective of detection is to detect a target from background or non-target materials, while the objective of classification is to classify targets buried at different depths. Three spectral transforms using binned energy windows can help alleviate the negative impact from background and suppress trivial spectral variation. However, their performance is sensitive to bin partition parameters including the number of bins and their bin-widths. We have developed a particle swarm optimization (PSO)-based automatic algorithm to determine these parameters. In this paper, we propose to apply multi-objective PSO to optimize both the detection and classification accuracy simultaneously. The experimental results demonstrate that the multi-objective PSO can achieve the balance between these two objectives, and it may provide even better individual performance than a single-objective PSO.

INTRODUCTION

Several approaches have been developed in detecting radioactive materials [1][2][3][4]. One of the most common and simple detection criteria used is the gross count (GC) of spectral counts within different spectral energy bands [1]. Spectral measurements of illicit sources or targets will have higher counts in specific energy bands, and this information can be used for detection. Another common method is to transform the spectra based on the difference between target and benign sources on certain energy bands. This method is referred to as the spectral comparison ratio (SCR) method [2][3]. If the ratio indicates that the unknown measurement is not similar to the benign measurement, the unknown measurement is likely that of the target. Principal Component Analysis (PCA) has also been utilized to analyze spectral measurements and major principal components will be used as new features for detection or classification purpose [4].

In our research, we investigate the solutions to the problem of detecting and classifying buried depleted uranium (i.e., the target) in soil at varying depths. The spectra are sparse due to short sensor dwell time, where spectral transformation using binned energy windows can help improve the performance and alleviate the interruption by background sources. But the problem of choosing appropriate energy channels for energy windows used in spectral transformation is still an open problem. For simplification purpose, we assume an energy channel is partitioned into one and only one window or bin; in other words, the partition is non-overlapping and for all the channels. Particle swarm optimization (PSO) is employed in this work, which is an evolutionary computation technique proposed and developed by Kennedy and Eberhart [5][6][7]. PSO has been widely used in many engineering optimization problems. It is proved to be a very efficient optimization algorithm by searching the whole problem space. In this research, two swarms of particles are employed to simultaneously select the optimal number of bins and the corresponding optimal bin-widths.

The method in [2] was developed to detect illicit sources from benign sources based on the anomaly test. It is a two-class classification problem for differentiating a target from a benign source. It is not suitable to the multi-class classification problem in this work. Therefore, in this paper, *k*-nearest-neighbor (*k*NN) classifier is used for two-class detection and multi-class classification. In the process of optimization, two different accuracy criterion functions can be used to achieve different objectives, i.e., detection and classification. In multi-objective PSO, a multi-objective function is employed to jointly optimize the two objectives, resulting in well balanced performance.

PROPOSED METHODS

Spectral transforms

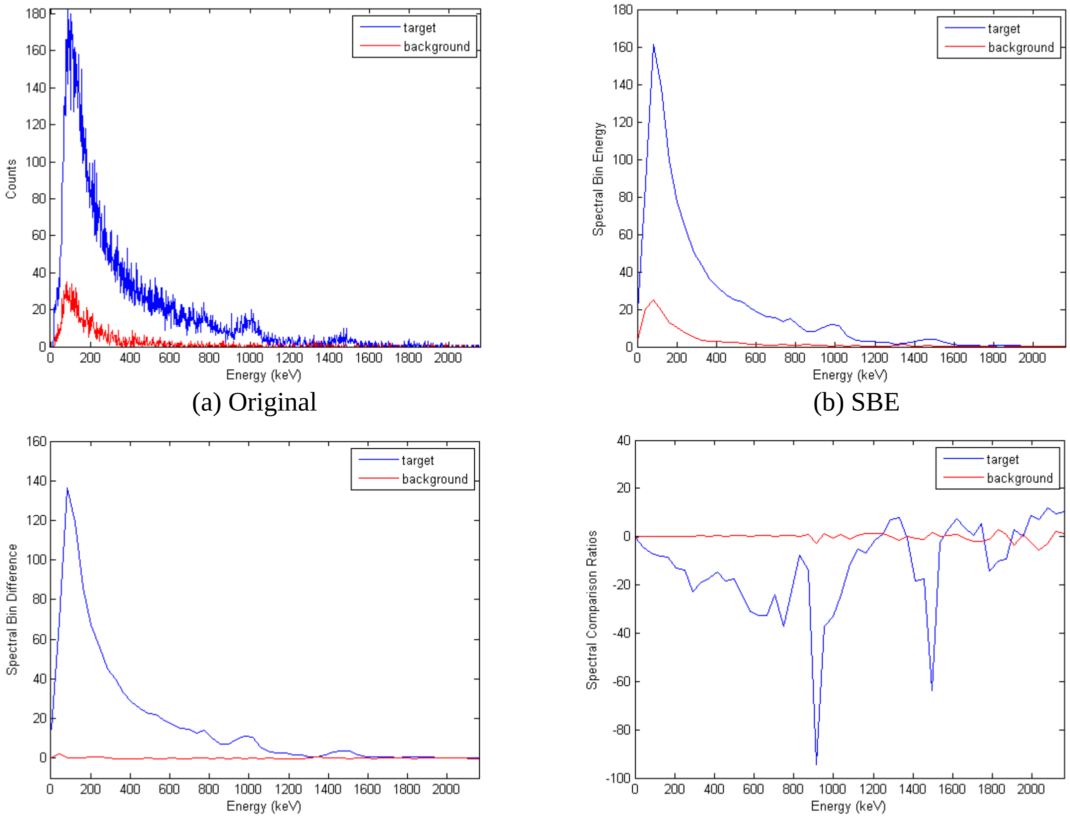
Most previous methods of radioactive target detection analyze the measured spectrum based on the total number of gamma-ray particle counts, i.e., GC. In our research, we utilize the entire energy spectrum. However, there are some difficulties when analyzing such "energy spectral signatures": 1) variability and uncertainty exist in the measurement that collection hardware always introduces to; 2) background has significant impact on the measurements, particularly when the target is buried. Thus, spectral transforms are applied so that sparseness and randomness in an original spectrum can be reduced while the discrepancy between target and background can be magnified.

Three spectral transformation methods are presented as follows for a spectrum partitioned into K non-overlapping bins. For the k th bin, the energy counts is for channel i denoted as $P(i)$. Spectral bin energy (SBE) sums the energy counts in each bin as shown in equation (1). Spectral bin difference (SBD) in equation (2) computes the sum of the counts in each bin subtract the counts of background in the same bin location. Spectral comparison ratio (SCR) in equation (3) computes how closely a spectrum matches that of background on the basis of spectral ratio in the same bin [2]. Fig.1 shows the target and background spectra before and after transformation.

$$S_{SBE}(k) = \sum_{i \in bin(k)} P(i) \quad \text{for} \quad k = 1,2,\cdots,K \tag{1}$$

$$S_{SBD}(k) = \sum_{i \in bin(k)} (P(i) - P(i)_{bkg}) \quad \text{for} \quad k = 1,2,\cdots,K \tag{2}$$

$$S_{SCR}(k-1) = S_{SBE}(1) - \frac{S_{SBE}(1)_{bkg}}{S_{SBE}(k)_{bkg}} S_{SBE}(k) \quad \text{for} \quad k = 2,3,\cdots,K \tag{3}$$



(a) Original (b) SBE

(c) SBD (d) SCR

Fig. 1 Original and transformed spectra of the target buried at 15cm.

Basic PSO

The PSO algorithm performs optimization in continuous, multi-dimensional search spaces. The search starts from random positions distributed in the problem space. It is very similar to other evolutionary computation algorithms in the three aspects: 1) it uses a large size of random particles as initials; 2) the optimum objective function is found by updating the generations; and 3) evolution updating involves the previous generations. The possible solutions called particles are flown through the problem space following the current optimal solution. The PSO is adopted in our research because of its fast convergence and global optimum searching ability.

The update of particles [6][7] is accomplished by using equation (4) which calculates the new velocity for each particles based on the previous velocity V_{id} , the particle's location (p_{id} or p_{Best}) that it has reached so far so best for the objective function and the particle's location among the globally searched solution (p_{gd} or g_{Best}) that has reached so far so best for the objective function. These particles are all potential solutions and their locations are updated by equation (5) in the solution hyperspace. There are two random numbers c_1 and c_2 are independently generated. And the inertia weight w is used as the scalar of previous velocity V_{id} which provides improved performance in various applications [7]. In equation (4), rand(.) denotes a generated random variable.

$$V_{id} = w \times V_{id} + c_1 \times \mathrm{rand}(\cdot) \times (p_{id} - x_{id}) + c_2 \times \mathrm{rand}(\cdot) \times (p_{gd} - x_{id}) \tag{4}$$

$$x_{id} = x_{id} + V_{id} \tag{5}$$

Multi-objective PSO

In reality, the overall detection (OD) accuracy and overall classification (OC) accuracy are the objectives we concern the most. We assume the data can be divided into two classes: target and non-target. OD measures percentage of the number of samples correctly classified into these two classes. In addition, the targets (and non-targets) buried at various depths can be seen as different classes, and OC measures the overall accuracy that samples are classified into their own class. Here, we can take into account both functions separately as the criterion function as equation (6) or (7). Or, we can maximize both simultaneously as equation (8), where the two objective functions are combined into one by employing weighting coefficients. Two weighting coefficients a_1 and a_2 are used to gauge the importance of certain objective functions within the optimization process. In our experiments, they are set as 0.5.

$$\max(OD) \tag{6}$$

$$\max(OC) \tag{7}$$

$$\max(a_1 OD + a_2 OC) \tag{8}$$

Performance evaluation

K-nearest-neighbor (k-NN) techniques are commonly used in pattern classification, which classifies objects into a predefined number of categories based on a given set of predictors [8]. Even in the situations when variables exhibit a highly nonlinear relationship between each other, k-NN may still be able to provide excellent performance. For simplicity and robustness, 1-NN is used in our experiments.

In order to eliminate the effects of biased selection of training and testing samples, the T-fold cross-validation is introduced where the fold number T is suggested to be chosen between 5 and 10 [9]. The T-fold cross-validation divides all the samples into T subsamples. Among the T subsamples, one subsample is taken for validation and the remaining $T-1$ subsamples are used as training data. The process is then repeated T times, with each of the T subsamples is used exactly once as the validation data. All the T results from the folds are averaged to produce a single estimation for criterion function. All samples are included for both training and validation, and each sample is used for validation exactly once.

EXPERIMENTS

Laboratory data was acquired by a 10×10×40 cm sodium iodide (NaI) scintillation detector. The measured spectra were taken over the energy range from 0 keV to 2160 keV. The target was a cylindrical object with 4.3 kg mass. The background conditions consisted of construction sand, and small uranium ore acted as a benign material. Buried at different depths of 15 cm, 23 cm, 30 cm, 45 cm, 60 cm, 75 cm, and 90 cm, the radiation energy from the target would decrease nonlinearly. Natural ore in a quart-size plastic bag was buried at 45 cm and 75 cm depth. For each class, there were 24 samples were taken evenly by four different dwell time. Sensor dwell time (i.e, counting period) was varied from 1 s, 0.5 s, 0.25 s, to 0.1 s. In our experiment, all the measurements were normalized into equivalent 1 s dwell time. In this experiment, 1-NN with 6-fold cross-validation was applied for the classification. OD was calculated when all the seven target classes were treated as a single class and natural ore and background as the other, while OC was computed when the ten classes were considered as individual classes.

If the bin-width is the same for all the bins, then exhaustive search is doable. To achieve the maximum OD, the optimal uniform bin-width for SCR, SBE and SBD were 7, 11, 11; to achieve the maximum OC, they became 7, 12, 12; to achieve the multi-objective optimization, they were 7, 12, 12. For varied bin-widths, the single-objective and multi-objective PSO were applied to determine the number of bins and bin-widths. 10 repeated runs were implemented, and the mean values were presented in Tables I, II, and III. Using GC, OD = 0.779 and OC = 0.555; using the original data without any spectral transform, OD = 0.900 and OC = 0.825.

Table I summarized OD when OD was the objective. For the three spectral transformation methods SBE, SBD and SCR, the uniform bin-width provided moderate OD because it fixed all bin-widths to the same and could not divide the spectrum adaptive to the energy peaks or features. However, the varied bin-width optimization would adjust the optimal number of bins and their corresponding widths so that an energy window could adaptively capture the interest energy peaks and combine them together. As the consequence, OD was improved. OC was derived with the corresponding bin parameters. Compared to GC and the case without spectral transform, both OD and OC were increased.

Table II summarized OC when OC was the objective. The varied bin-width PSO still provided a higher accuracy than the exhaustively searched uniform bin-width. Again, OD was derived with the corresponding bin parameters. Comparing Table I and II, we can see that our optimization method enhanced the desired accuracy function as we set it as our criterion function in the optimization process. This is why the OD in Table I is larger than the counterpart in Table II, and OC in Table II is larger than that in Table I.

Table III summarized the multi-objective function value, retrieved OD and OC, when the multi-objective function was the searching criterion. Compared the results in Table I and II, we notice that OD values were close to those when OD was the single objective to be optimized; similarly, OC values were close to those when OC was the single objective.

For PSO, the mean values of 10 runs were presented in the tables. To better show the performance statistics, boxplots with the information of mean and standard deviation were drawn in Fig. 2. They further confirmed that the multi-objective PSO (denoted as “OD/OC’) provided the comparable performance in the one optimized by a single-objective PSO (denoted as “OD” or “OC”). However, as shown in Fig. 2(c), the multi-objective PSO provided a better joint performance.

Table I. The resulting performance when the objective is overall detection accuracy

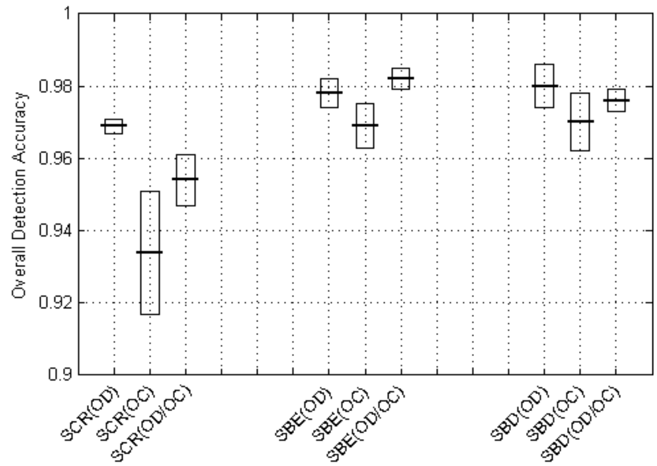
	OD	OC
Uniform bin-width SCR	0.879	0.788
Uniform bin-width SBE	0.946	0.867
Uniform bin-width SBD	0.946	0.867
Varied bin-widths SCR (PSO)	0.969	0.840
Varied bin-widths SBE (PSO)	0.978	0.904
Varied bin-widths SBD (PSO)	0.980	0.908

Table II. The resulting performance when the objective is overall classification accuracy

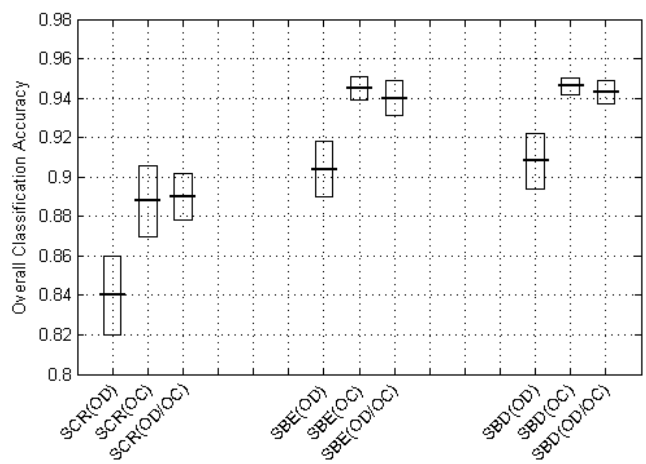
	OD	OC
Uniform bin-width SCR	0.879	0.788
Uniform bin-width SBE	0.942	0.875
Uniform bin-width SBD	0.942	0.875
Varied bin-widths SCR (PSO)	0.934	0.888
Varied bin-widths SBE (PSO)	0.969	0.945
Varied bin-widths SBD (PSO)	0.970	0.946

Table III. The resulting performance when the multi-objective function is to be optimized

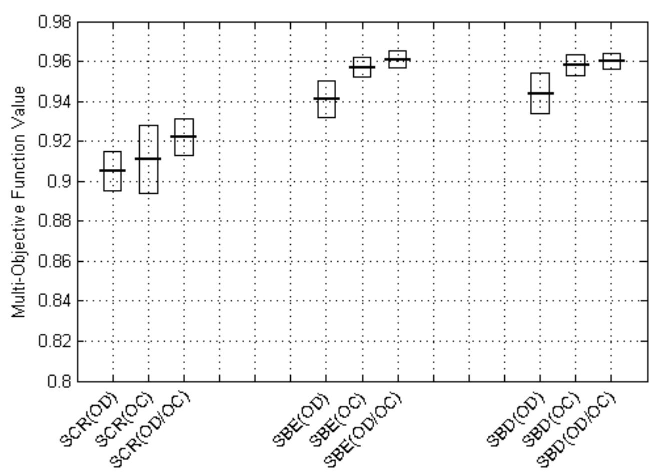
	Multi-objective Function (0.5 OD + 0.5 OC)	OD	OC
Uniform bin-width SCR	0.833	0.879	0.788
Uniform bin-width SBE	0.908	0.942	0.875
Uniform bin-width SBD	0.908	0.942	0.875
Varied bin-widths SCR (PSO)	0.922	0.954	0.890
Varied bin-widths SBE (PSO)	0.961	0.982	0.940
Varied bin-widths SBD (PSO)	0.960	0.976	0.943



(a) Detection Accuracy (OD)



(b) Classification Accuracy (OC)



(c) Multi-objective function value (0.5 OD + 0.5 OC)

Fig. 2 Boxplots for PSO-based bin optimization.

CONCLUSION

In this paper, we propose an adaptive optimization system with PSO to automatically determine the optimal number of bins and the corresponding optimal varied bin-widths for energy spectral transformation. It can provide better performance than using uniform bin partitions. To achieve high detection and classification accuracy simultaneously, the system deploys a multi-objective PSO, which can well balance the detection and classification performance when both are of great concern in a practical application.

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