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Munitions Classification using an Acoustic Resonance Spectroscopic Technique

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Abstract

A nondestructive evaluation technique for classifying artillery munitions is presented. This technique, based on acoustic resonance measurements, has been successfully demonstrated on a wide variety of high explosive and chemical munitions. The technique consists of building templates of spectral features from sets of known munitions. Spectral features of unknown munitions are compared with a library of templates, and the degree of match between the features and the templates is used to classify the munition. This paper describes the technique, including the feature extraction, clustering and classification algorithms.

1 Introduction

In support of the Bilateral Chemical Weapons Agreement between the United States and Russia, Los Alamos National Laboratory has developed a nondestructive evaluation (NDE) technique that discriminates between different types of artillery munitions. This NDE classification technique allows on-site inspectors to rapidly classify the munitions as chemical or high explosive, and furthermore discriminates between various subclasses of these types of munitions. It provides an alternative to time consuming or hazardous techniques such as drill-and-sample. The technique, based on Acoustic Resonance Spectroscopy (ARS), has been successfully field tested on a wide variety of munitions [1].

Acoustic Resonance Spectroscopy is the study of the mechanical resonance structure of objects. Objects that are composed of elastic materials have natural modes of vibration. These modes are standing

waves in the object and can be excited by application of a vibration at the appropriate frequencies. These frequencies, called resonant frequencies, are determined by the geometry of the object as well as its material composition. The munitions specified in the bilateral agreement have unique sets of resonant peaks in their acoustic spectrum. These peaks, as previously noted, are related to the mechanical structure of the munition and can be used to uniquely identify a particular class of munition. For example, munitions with thinner walls tend to produce acoustic resonances at higher frequencies than those with thicker walls. Munitions filled with solids tend to produce broader acoustic resonances than those filled with a liquid. Likewise, munitions filled with viscous liquids tend to produce wider resonant peaks than those with lighter liquids. It is this type of difference in acoustic spectra that provide the foundation of the ARS classification technique.

The ARS classification technique constructs templates of spectral features from known munition classes and compares the template with the spectral features of an unknown munition. To construct a template, spectral data from each munition in the training set is smoothed and the relevant spectral features are extracted. A feature consists of two components: the frequency of a resonant peak, and a measure of the sharpness of the peak. The features from all munitions in the training set are clustered so that the variance of each cluster is minimized. These clusters form a template for a particular class of munition. When an unknown munition is classified, its spectral features are extracted and compared with a library of available templates. If the spectral features of the munition and a template in the library are closely matched, the munition is declared to belong to the class associated with that template. In the sequel, we describe the classification technique in detail.

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2 Measurement System

The acoustic spectra of a munition is measured by a system composed of a signal synthesizer/receiver, digitizer, a pair of piezoelectric transducers, and a control computer. The frequency synthesizer generates a stepped frequency sinusoid from f_{start} to f_{stop} where f_{start} is typically set to 1 kHz and f_{stop} is typically set to 30 kHz. The frequency increment of the stepped sinusoid is adjustable, but nominally set to $f_{inc} = 25$ Hz and the dwell time on each tone is $1/f_{inc}$ seconds. A piezoelectric transducer couples the energy from the signal synthesizer into the munition. The power applied to the transducer is approximately 1 mW, which induces vibrations in the munitions with amplitudes on the order of 10 nanometers. A second piezoelectric transducer is used to receive the response of the munition. The output signal is quadrature demodulated with a homodyne receiver, and the in-phase and quadrature-phase baseband signals are digitized with 14 bits of resolution. The piezoelectric transducers are housed in a hand held mount that magnetically attaches itself to a munition. The entire system is small, portable, and is battery powered for up to five hours of continuous field use. Finally, the control computer has a custom-built user interface that controls operation of the entire system.

3 Pattern Recognition Algorithms

Several different algorithms are described here. The algorithms are used for two purposes: to construct templates from known munitions and to test unknown munitions. Templates are constructed by collecting spectral data from ten to twenty known munitions, extracting spectral features from the data and clustering the features to form a template for that class of munition. Unknown munitions are classified by measuring the unknown's acoustic spectrum, extracting its spectral features and comparing the features to a library of templates. The algorithms used for these tasks are described below.

3.1 Feature Extraction

A raw measurement is a sequence of N complex-valued samples of spectral data $\tilde{X}_r(n) + j\tilde{X}_i(n)$, where $n = 0, \dots, N-1$ and $N = (f_{stop} - f_{start})/f_{inc}$. An M -point unity-area Hamming window $w(n)$ is convolved with the raw data to produce a smoothed version $X(n) = \tilde{X}(n) * w(n)$. In order to increase the statistical reliability of the measurement, the length of

the window is set so that $M \gg 1$. For a typical measurement, the value of M is set to $M = 32$. The magnitude of the smoothed data, $S(n) = \sqrt{X(n)X^*(n)}$, is computed and then normalized. Figure 1 illustrates a normalized magnitude plot of raw data, and Figure 2 illustrates a plot of processed data.

Feature extraction consists of locating peaks in the processed spectral data, determining the frequencies of the peaks, f_i , and their quality factors, q_i . The frequencies of the peaks are computed by first-order differencing the processed spectral data $S'(n) = S(n) - S(n+1)$, $0 \leq n \leq N-2$, and then locating zero crossings in the difference sequence. The frequencies at which the difference sequence $S'(n)$ is equal to zero correspond to peaks in $S(n)$. The current implementation finds the first 80 peaks, a number that has been found to be adequate. Figure 3 illustrates the locations of peaks extracted from a measurement superimposed over the processed spectrum.

The quality factor of the i^{th} peak, q_i , is determined as follows. We define the quality factor Q of a peak to be $Q = H/B$ where H is the height of the peak and B is the width of the base of the peak. The value of B of the i^{th} peak is determined by starting at the frequency of the peak, f_i , and searching in the direction of increasing frequency for the frequency f_u associated with first valley above the peak. The same search is performed in the direction of decreasing frequency for the frequency f_l associated with the first valley below the peak. The width of the base is defined as $B = 2 \times \min(|f_i - f_u|, |f_i - f_l|)$. The height H is defined to be the difference between the magnitude of the peak and the magnitude of the closest valley, $H = S(f_i) - S(f_v)$ where f_v is either f_u or f_l , whichever corresponds to the frequency used in the width calculation.

Since a measurement typically contains many features, some of which are not significant, only features with large values of Q are accepted for further processing. All other features are rejected as being insignificant. The features are sorted in order of increasing q_i , and the first 50 features are selected. Thus, the feature extraction algorithm produces a set of features where the i^{th} feature consists of a frequency and a quality factor, (f_i, q_i) . Figure 3 illustrates the output of the feature extraction algorithm for the data depicted in Figure 2.

3.2 Clustering and Template Construction

The feature extraction algorithm generates a set of N features $F = \{(f_i, q_i), i = 1, 2, \dots, N\}$ for each

measurement. To build a template, measurements on multiple objects are required. Thus, a featureset F_j , where $j = 1, 2, \dots, M$ is constructed from the M measurements. A clustering algorithm is used to form clusters of features so that templates for the object class can be constructed. The idea behind the clustering algorithm is to form clusters with the smallest possible variance. A brute force implementation of this approach is computationally complex if the featureset is large, but modifications of the basic idea allow more tractable solutions.

The computational complexity of the clustering algorithm is reduced by forming clusters from features within a narrow frequency range. Only features that are close in frequency are clustered. Of these clusters, only the ones with minimum variance are accepted. Specifically, the clustering algorithm begins by finding the maximum and minimum frequencies in the featureset F_j , $f_{max} = \max_{f_i} \{F_j\}$ and $f_{min} = \min_{f_i} \{F_j\}$. A frequency window that has a frequency span that is a fraction of the frequency range of the featureset is computed $\Delta W = W_j(f_{max} - f_{min})$, where W_j is a scaling factor typically set to 0.025. The center frequency of the window is shifted by a small fraction of the window's width each iteration so that $W_k = f_{min} + kW_i\Delta W + \Delta W/2$ where W_i is an increment factor set to $W_i = 0.1$. The increment index k is restricted to the range $0 \leq k \leq N_w$ where $N_w = \frac{1}{W_i}(\frac{1}{W_j} - 1) - 1$.

Once the window is in place, the featureset is scanned to find features that lie within the window. A family of sets C_k is formed such that $C_k = \{(f_i, q_i) : (f_i, q_i) \in F_j, W_k - \Delta W/2 \leq f_i \leq W_k + \Delta W/2\}$. If fewer than 80% of the measurements contribute features to C_k , the family of sets is abandoned, and W_k advances to the next iteration. If the inclusion criterion has been met, the algorithm finds the set of features that produce the smallest frequency variance $\sigma_k^2 = \min_{\sigma_j^2} \{C_k\}$. An exhaustive search is performed by forming all possible combinations of features, taking one feature from each measurement contained in C_k . Once the set of features with the smallest frequency variance has been found, the mean of the frequencies in the cluster is computed f_k , and features that have frequencies less than the mean frequency $f_i < f_k$ are prohibited from forming new clusters. This action prevents features that are on opposite fringes of a cluster from combining into a new cluster.

Four quantities are derived from each cluster: the mean of the frequencies in the cluster f_k , the standard deviation of the frequencies in the cluster Δf_k , the mean of the quality factors in the cluster q_k , and

the standard deviation of the quality factors in the cluster Δq_k . These four quantities ($f_k, \Delta f_k, q_k, \Delta q_k$) adequately characterize the cluster for classification purposes. It has been observed that clusters tend to be narrow in frequency relative to quality factor. Ideally, clusters would be narrow in both quantities. Additional research is required to develop better algorithms for finding a quality factor that narrows the clusters in this dimension, or identify other types of features that provide more compact clusters.

After all clusters have been found, several selection criteria are applied to determine the clusters used to construct a template. First, the widths of the clusters in frequency are sorted into ascending order, $\Delta f_1 < \Delta f_2, \dots, \Delta f_N$, where N is the number of clusters constructed. The sequence of cluster widths are first-order differenced, and a running mean of the differences is computed. The reasoning behind this procedure is the observation that if the frequency widths of the clusters are listed in increasing order, a large jump in magnitude often occurs after the first few clusters. The location of this jump provides a demarcation between clusters associated with strong resonant peaks and clusters that the algorithm built out of smaller features. Clusters beyond the point where the next difference exceeds a threshold (four times the running mean) are excluded from the template. Clusters within the threshold are used as the template. Occasionally, no obvious jump occurs in the frequency width magnitude. In this case the first 16 clusters are used to construct the template. Figure 3 illustrates the clusters found by the clustering algorithm for five measurements on the same class of objects used in the previous figures.

3.3 Munition Classification

Templates are used to determine if an object, as represented by its measured features, belongs to the class of objects whose features were used to construct the template. Comparison between the features of an object and a template is performed by a template matching algorithm. The output of the algorithm is a number that represents the degree of match between the features extracted from a measurement and the template.

The template matching algorithm counts the number of frequency features from a measurement that are within frequency windows derived from cluster parameters in the template. Each frequency window is centered at the mean frequency of one entry in the template, and has a width equal to the width of the associated cluster. Once a feature has been counted

	GH55	HO55	HE55	S55V	VX55
GH55	0.777	0.222	0.666	0.277	0.166
HO55	0.055	0.666	0.388	0.444	0.222
HE55	0.166	0.222	0.555	0.222	0.222
S55V	0.111	0.444	0.166	0.444	0.055
VX55	0.222	0.222	0.388	0.222	0.666

Table 1: Hit ratios for a single measurement of a munition type (rows) for munition templates (columns).

as a "hit," it is prohibited from contributing to hits on other windows. After all features have been scanned for hits, a hit ratio, i.e. the ratio of the number of features in the measurement that match features in the template to the number of features in the template, is computed. The larger the hit ratio the better the match between the features of a measurement and the template. In order to account for possible frequency shifts of a measurement's features, which can occur if the fill level of the munition differs from those used to construct the template, the frequency windows are shifted by a slight amount (three times the bin width of the measurement) and the hit ratio is again computed. The hit ratio for each shift is computed, and the largest hit ratio of all shifts is reported.

4 Preliminary Results

The algorithms presented in this paper were developed and tested with ARS data collected at the Tooele Army Depot. Although the lack of data prevented a statistical analysis of the algorithms' performance, two examples are given that illustrate the type of results we obtained with the algorithms. The designators, shell sizes and compositions of the shells discussed in the examples are: GH55, 155 mm GB nerve agent (high purity); HO55, 155 mm Mustard gas; HE55, 155 mm high explosive; VX55, 155 mm VX nerve agent; S55V, 155 mm VX physical surrogate (designed to match the mechanical properties of VX55).

In the first example, a template for each munition class was constructed using seven randomly selected measurements from each class. Another randomly selected measurement from each class was classified against the templates. The hit ratio for each template is listed in Table 1.

The example illustrates how the features from a particular munition match a template from the same class of munition and also match templates created

from other munitions. The only ambiguous result occurs when the S55V measurement matches the HO55 and S55V templates equally well. The classification error is probably caused by a bad measurement, which in turn might be due to poor transducer placement or poor transducer coupling.

As another example, five measurements from each munition class were compared to the five templates. The GH55, HE55, and S55V shells were correctly identified on all five trials. The HO55 and VX55 shells were correctly identified on four of the five trials and misidentified once each. While these results do not represent an exhaustive test of the algorithms, they are indicative of the results we have obtained. In the vast majority of trials, a munition matched the template of its class either best or second best.

5 Summary

The ARS classification technique described in this paper has been field tested on a wide variety of munitions. The technique is based on the acoustic resonance structure of the munition and has shown good discrimination ability. A field instrument constructed to implement the technique will be used by the On Site Inspection Agency to verify compliance with the Bilateral Chemical Weapons Agreement between the United States and Russia.

References

- [1] D. N. Sinha, "Acoustic Resonance Spectroscopy," IEEE Potentials, April 1992, vol. 11, No. 2, pg. 10.

Figure 1: Normalized magnitude plot of raw acoustic spectral data.

Figure 2: Raw acoustic data smoothed with a 32-point, unity-area Hamming window.

Figure 3: Normalized magnitude plot of raw spectral data with extracted features denoted by 'o', and features selected by the clustering algorithm denoted by '+'.
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Figure 4: Plot of the featureset of five measurements. Clusters found by the clustering algorithm are circled.

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