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Title:

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DISCRIMINATION OF LIQUID AND SOLID FILLED MUNITIONS

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A Pattern Recognition Algorithm for the Blind Discrimination of Liquid and Solid filled Munitions *

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Abstract

A new pattern recognition algorithm is described for the nondestructive evaluation of stockpiled munitions. The algorithm performs blind classification on munitions to determine if they are liquid-filled (chemical) or solid-filled (conventional) munitions. The algorithm uses attributes of the acoustic spectrum of the munition under inspection to perform the discrimination. Results are presented on the performance of the pattern recognition algorithm on a large set of data collected from chemical and conventional munitions at the U. S. Tooele Army Depot.

1. Introduction

Los Alamos National Laboratory has developed a nondestructive evaluation system that classifies chemical munitions according to agent [1], [2]. The system is slated for use as a verification tool in the Chemical Weapons Convention, a multilateral chemical weapons agreement scheduled to take effect in the near future. The system, based on acoustic resonant spectroscopy (ARS), has been successfully tested on a wide variety of U. S. chemical munitions [3], [4], [5]. This paper describes a new algorithm designed to discriminate between liquid and solid filled munitions. A liquid-solid discrimination algo-

rithm is highly desirable for treaty verification since it allows on-site inspectors to rapidly survey munition depots suspected of harboring chemical (liquid-filled) munitions.

An important distinction between the liquid-solid discrimination algorithm and the munition classification algorithm is that the former performs blind classification whereas the latter requires training. Blind classification relieves inspectors of the time consuming task of locating and identifying munitions for a training set. In addition to robustness, the design requirements for the discrimination algorithm are that it use the same measurements, and execute on the same system, as the munition classification algorithm.

The munition classification algorithm presented in [1] and [2] exploits the acoustic spectrum of the munition under inspection. Spectral features are extracted from the acoustic spectra of known munition classes. 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 to a library of templates. If the match between the spectral features of the munition and a template in the library is close enough, the munition is declared to belong to the class associated

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Figure 1: The upper graph is a plot of the magnitude of the acoustic resonant spectrum of a liquid-filled munition. The lower graph is a plot of the magnitude of the acoustic resonant spectrum of a solid-filled munition.

with that template. The ARS instrument is designed for field use, and consists of a portable battery-powered instrument package along with a notebook computer.

The liquid-solid discrimination algorithm also exploits the acoustic resonant spectrum of the munition under inspection. However, as discussed in the next section, the features used in the liquid-solid discriminator differ significantly from those used in the munition classifier.

2. Feature Extraction

The key to successful pattern recognition lies in the selection of appropriate features. In this discrimination problem two features are extracted from each spectrum: the average valley-to-valley widths of peaks in the spectrum, and the ratio of the area of the spectrum above 10 kHz to the area of the spectrum below 10 kHz. Munitions filled with solids tend to have larger dampening coefficients than munitions filled with liquids. As a result, the resonant peaks of solid-filled munitions tend to be wider than resonant peaks of liquid-filled munitions. Figure 1 illustrates the peak-width feature with exemplar plots of the acoustic spectra of liquid- and solid-filled 155mm munitions. The upper graph is a magnitude plot of the acoustic spectrum of a munition filled with VX, a

liquid nerve agent. The lower graph is a magnitude plot of the acoustic spectrum of a munition filled with white phosphorous, a solid that produces smoke on detonation. Notice how peaks in the lower graph are indeed wider than those in the upper graph. As indicated in the sequel, the peak-width feature is a key to the successful discrimination of liquid- and solid-filled munitions.

The basis for the area feature is also illustrated in Figure 1. Note that the area of the spectrum between 5 and 10 kHz is larger in the solid-filled munition than in the liquid-filled munition. This region is populated by a many overlapping resonance modes and tends to be more pronounced in solid-filled munitions than in liquid-filled munitions. As a result, the ratio of the area of the spectrum above 10 kHz to the area of the spectrum below 10 kHz tends to be smaller in solid-filled munitions than in liquid-filled munitions.

As reported in [1], the acoustic spectrum produced by the ARS instrument consists of a complex-valued amplitude $\hat{X}(n)$ for each frequency $f(n)$, $n = 0, \dots, N-1$. The frequency range of the instrument is typically set to $1\text{ kHz} \leq f(n) \leq 30\text{ kHz}$, and the frequency increment between spectrum samples is $\Delta f = 25\text{ Hz}$. Initial processing of the spectrum consists of smoothing the magnitude of the spectrum with a unity-area Hamming window:

$S(n) = |\tilde{X}(n)| \otimes h(n)$. The important point here is to select a window sufficiently wide to reduce noise in the spectrum while at the same time narrow enough to preserve features of interest (peak widths). After experimenting with a variety of window widths, a window with a bandwidth on the order of 200 Hz was selected.

Peak-width features are found by locating peaks and surrounding valleys within $S(n)$ and computing the valley-to-valley width of the peak. A simple and computationally efficient algorithm is employed to locate spectral peaks and valleys. Estimation of peak parameters begins by performing a difference-sign-difference operation on $S(n)$ to form a new sequence $\tilde{S}(n) = (\Phi(S'(n)))'$, where the prime symbol denotes the differencing operation and Φ is the signum function. The sequence $\tilde{S}(n)$ consists of the elements $\{-2, -1, 0, 1, 2\}$ where -2 indicates the location of a peak, 2 the location of a valley, 1 the location of the edge of a plateau (concave up), and -1 the location of a plateau (concave down). Zeros represent regions of positive or negative slope and are not used.

Estimating the relevant parameters now consists of locating indices in $\tilde{S}(n)$ that correspond to a particular feature, and applying those indices to $f(n)$ thereby locating the frequency of the feature. Denote the frequency of the i^{th} peak as $f_p(i)$, the frequency of the leading valley as $f_a(i)$, and the frequency of the trailing valley $f_b(i)$. The frequencies of peaks are found by first forming the set of indices $P = \{k | \tilde{S}(k) = -2\}$ from $\tilde{S}(n)$, and then forming a set from $f(n)$, $F = \{f(n+1) | n \in P\}$, where the i^{th} element of F is the i^{th} peak. (Due to the differencing operations an index shift of +1 is required to align locations in $f(n)$ with those in $\tilde{S}(n)$.) The frequencies of the leading and trailing valleys of the peak are found in a similar manner. The valley-to-valley width of the peak is then estimated as $w(i) = f_b(i) - f_a(i)$. The peak-width feature of the spectrum is the average of all peak widths, $W = \langle w(i) \rangle$.

The area feature is the ratio of the area of the spectrum between 1 kHz and 10 kHz, and the area of the spectrum between 10 kHz and 30 kHz. The area feature is found by summing spectral amplitudes over the appropriate bands. The feature is

Figure 2: Decision boundary and features from ARS measurements of liquid- and solid-filled munitions. The circles represent features from liquid-filled munitions while the crosses represent features from solid-filled munitions.

computed as:

$$A = \frac{\sum_{n=N_f}^{N-1} \tilde{S}(n) \Delta f}{\sum_{n=0}^{N_f-1} \tilde{S}(n) \Delta f} \quad (1)$$

The value for N_f in (1) is selected so that $f(N_f) = 10$ kHz, and $\Delta f = 25$ Hz. A feature vector is formed, $F = [W, A]$, and is used for the discrimination. Figure 2 illustrates a scatter plot of the features obtained from a data set of 256 liquid-filled munitions and 200 solid-filled munitions.

3. Discrimination Algorithm

The liquid-solid discrimination is performed by a Bayes binary classifier [6]. Recall that for classes ω_1 and ω_2 , the general form of the hypothesis

rule is: If the inequality

$$\frac{p(X|\omega_1)}{p(X|\omega_2)} > \frac{P(\omega_2)}{P(\omega_1)} \quad (2)$$

is true, then choose class ω_1 , if the inequality is false, choose class ω_2 , and in the case of equality choose either class. In inequality (2), $p(X|\omega_1)$ is the probability density of the features conditioned on class ω_1 , (and similarly for $p(X|\omega_2)$), and $P(\omega_1)$ is the *a priori* density function for ω_1 (likewise for $P(\omega_2)$).

After studying scatter plots of features extracted from liquid- and solid-filled munitions (cf. Figure 2), it appeared reasonable to approximate the distributions of the features as Gaussians. Specializing the hypothesis rule by applying the natural logarithm to (2) and assuming Gaussian distributions yields the decision rule: If the inequality

$$\begin{aligned} & (R - m_1)^T K_1^{-1} (R - m_1) \\ & - (R - m_2)^T K_2^{-1} (R - m_2) \\ & > 2 \log \eta + \log |K_2| - \log |K_1| \end{aligned} \quad (3)$$

is true, then choose class ω_1 , if the inequality is false choose class ω_2 , and in the case of equality choose either class. In inequality (3), R is a measurement vector consisting of features extracted from the measurements, m_1 is the mean vector of class ω_1 (similarly for m_2), K_1 is the covariance matrix of class ω_1 (likewise for K_2), and $\eta = P(\omega_1)/P(\omega_2)$. For the experimental results reported below, η was set equal to the number of measurements in class ω_1 divided by the number of measurements in class ω_2 . In the field instrument, η is set equal to unity so that the term $2 \log \eta$ vanishes.

Discrimination now consists of applying features extracted from munitions under inspection to classifier (3). The parameters for the classifier, m_1 , K_1 , m_2 and K_2 , were obtained from a large set of acoustic spectra obtained from U. S. liquid- and solid-filled munitions. Experimental results of applying the discrimination algorithm to this data set are discussed next.

4. Experimental Results

The discrimination algorithm described above was tested on munition data collected at the U. S. Tooele Army Depot. The data set consists of 256 measurements from 155mm munitions filled with VX and GB (liquid nerve agents) and 200 measurements from 155mm munitions filled with TNT, Comp-B (solid high explosives) and white phosphorous (a solid smoke agent). Several experiments were conducted to assess the performance of the discrimination algorithm. The experiments and results are summarized below.

Experiment 1: This experiment tested the validity of the feature extraction and discrimination algorithms. The decision boundary, i.e., the locus of points of equality in (3), was computed using mean and covariance estimates from the entire data set. The entire data set was then classified using (3). A scatter plot of features from the munitions, along with the decision boundary, is illustrated in Figure 2. The circles represent features from liquid-filled munitions while the crosses represent features from solid-filled munitions. In this experiment, all of the measurements were correctly classified, for an error rate of 0% and a reliability of 99.5% at 90% confidence.

Experiment 2: In this experiment, a data set consisting of 100 randomly selected liquid measurements and 100 randomly selected solid measurements was formed. The means and covariances of this data set were used in (3), and the data set classified. The decision boundary did not substantially change, but one liquid measurement was misclassified as a solid. The overall error rate for this experiment is 0.5%, with a reliability of 98.1% at 90% confidence.

Experiment 3: This experiment assessed the ability of the algorithm to perform blind discrimination. The means and covariances of a data set consisting of 50 randomly selected liquid measurements and 50 randomly selected solid measurements were used to set classifier parameters. A second data set of 50 randomly selected liquid and 50 randomly selected solid measurements were classified. One liquid measurement was misclassified as a solid for an error rate of 1%. The reliability for this experiment is 96.2% at 90% confidence.

5. Conclusions

A new algorithm is described for the blind discrimination of liquid- and solid-filled munitions. The algorithm uses features extracted from the acoustic resonant spectrum of the munition under inspection. Two features are extracted from the spectrum: The average width of resonant peaks in the spectrum, and the ratio of the area of a lower spectral band to the area of an upper spectral band. A Bayes binary classifier, specialized to Gaussian distributions, is used for the discrimination. The discrimination algorithm has been successfully tested on data collected from U. S. chemical and conventional munitions.

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