A SUBSPACE SIGNAL PROCESSING TECHNIQUE FOR CONCEALED WEAPONS DETECTION

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ABSTRACT

Concealed weapons detection is one of the greatest challenges facing national security nowadays. Recently, it has been shown that each weapon can have a unique *fingerprint*, which is a set of electromagnetic (EM) resonant frequencies determined by its size, shape, and physical composition. Extracting the resonant frequencies of each weapon is one of the major tasks of any detection system. In this paper, we model the reflected signal from each object as a summation of sinusoidal signals, each at certain frequency equal to one of the object's resonant frequencies. Using this model, we propose a detection approach that is based on a modified version of the MUltiple SIgnal Classification (MUSIC) algorithm. We show by simulations that each object can be represented using a two-dimensional vector, which consists of its two major resonant frequencies.

Index Terms— MUSIC algorithm, natural resonance, signal processing, subspace algorithms.

1. INTRODUCTION

Concealed weapons detection in public places such as airport concourses, passenger train terminals, and shopping center entrances is one of the greatest challenges facing national security. Most of the current weapons detection systems, such as portable instruments and walk through detectors, have several drawbacks. Portable instruments endanger their users as they require close proximity to the person being searched, while walk through detectors require crowds of people to be channeled to choke points, which cause large delays. Thus, there is an urgent need for a new concealed weapons detection system which detects weapons from a distance in a quick and efficient way.

Recently, there have been demonstrations that weapons have *fingerprints* just like people do [1], [2]. In [2], it has been shown that each weapon can have a unique signature, which is a set of electromagnetic (EM) resonant frequencies determined by its size, shape, and physical composition. Based on this fact a detection system can be built, which first excites the object's natural resonance then characterizes it using its reflected frequency response.

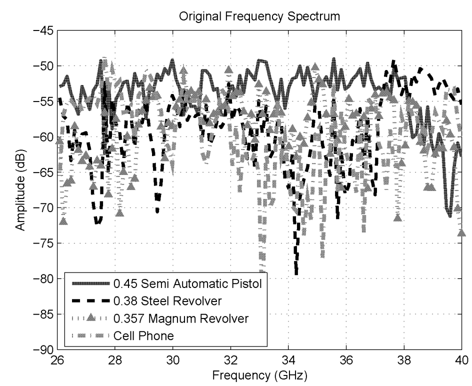

Fig. 1. Measured frequency response of various objects.

Fig. 1 depicts the amplitude of the frequency spectrum reflected from different objects, which are 0.45 semi-automatic pistol, 0.38 steel revolver, 0.357 magnum revolver, and a cell phone. Due to the noise and multipath effects, the response of each object is not distinguishable. In other words, there is no indication of certain resonant frequencies, where there exist clear peaks. Thus, the main *goal* of this paper is to develop a non-intrusive efficient signal processing algorithm, which extracts each weapon's signature in an efficient and quick way.

Various signal processing techniques have been applied to extract each object's signature in both time and frequency domains. In [1], Prony's method was used to extract the signature of each object in the time domain. However, its performance is affected dramatically by its window width and starting location. In [2], the matched filter technique was implemented to differentiate between different weapons in the frequency domain. As shown in Fig. 1, it is difficult to characterize each object's response based on its shape. In addition, this approach requires the detector to store an analog version

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of the frequency spectrum of each object as its filter response, which requires huge storage capacity.

The major *contribution* of this paper is the signal model we are proposing to characterize the natural resonance of the interrogated objects. Due to the natural resonance phenomenon of an object, its frequency spectrum should have clear peaks at its resonant frequencies. This fact corresponds to having a number of time-domain sinusoidal signals, each operating at one of the object's resonant frequencies. Therefore, we model the reflected signal as a noisy version of summation of a number of sinusoidal signals.

Based on the proposed model, the object's response forms a space, which can be decomposed into two orthogonal subspaces, namely, a signal subspace and a noise subspace. The signal subspace consists of all the resonant frequencies of the reflected signal, while the noise subspace consists of all the frequencies other than the resonant ones. For a composite signal consisting of a number of sinusoidal signals, the subspace methods, particularly the MUltiple SIgnal Classification (MUSIC) [3]-[6], can determine accurately the frequencies of the individual sinusoidal signals. Thus, the main principle of our proposed detection approach is to apply a modified version of the MUSIC algorithm to extract its resonant frequencies.

The rest of this paper is organized as follows. In the next section, we describe the proposed signal model including the modified MUSIC algorithm. In Section 3, we present the complete weapons detection system and the block diagram of the detection approach. To illustrate the performance of the proposed detection algorithm, we present some simulation results in Section 4. Finally, Section 5 concludes the paper and presents future work.

2. PROPOSED SIGNAL MODEL

In this section, we describe our proposed signal model, which can be used to represent the signal reflected from any object. We assume that the interrogated object has K resonant frequencies at frequency f_i with magnitude F_i, $i = 1, \cdots, K$. Thus, it is expected that the measured frequency spectrum of the signal reflected from this object should have K clear peaks at these frequencies. This corresponds to having a time-domain signal $x(t)$, which can be expressed as

$$x(t) = \sum_{i=1}^{K} F_i \exp(-2\pi j f_i t) + n(t) \ , \tag{1}$$

where $n(t)$ is an additive noise. The signal $x(t)$ can be used to form a space that can be decomposed into two orthogonal subspaces, namely, a signal subspace and a noise subspace as follows.

By sampling the composite signal at M different time instants $t_i, i = 1, \cdots, M$, we can represent the M data samples as

$$x = AF + n \ , \tag{2}$$

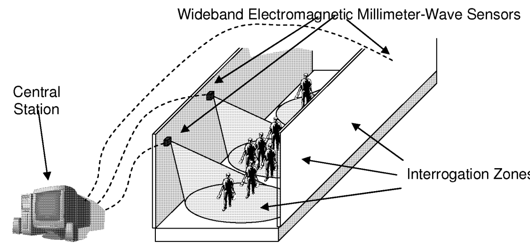

Fig. 2. Complete concealed weapons detection system.

where $x = [x_1\, x_2 \cdots x_M]^T$ is the data vector, T denotes the transpose, and $x_i = x(t_i), i = 1, \cdots, M$. The matrix $A = [a(f_1)\, a(f_2) \cdots a(f_K)]$ consists of the steering vectors $a(f_k) = [\exp(-2\pi j f_k t_1) \exp(-2\pi j f_k t_2) \cdots \exp(-2\pi j f_k t_M)]^T$. Finally, the vector $F = [F_1\, F_2 \cdots F_K]$ represents the magnitudes of the signals and $n = [n_1\, n_2 \cdots n_M]$ is the noise vector.

The MxM covariance matrix of the data vector x can be calculated as

$$R = (x - \mu)(x - \mu)^H \ , \tag{3}$$

where μ is the mean of the vector x and H denotes the conjugate transpose. We employ the eigenvalue decomposition for the covariance matrix R and calculate its eigenvalues and eigenvectors. In addition, the eigenpairs are ordered in an ascending order according to the eigenvalues. The first $M - K$ eigenvectors, which correspond to the smallest $M - K$ eigenvalues, span the noise subspace while the last K eigenvectors form the signal subspace. Then matrix E, which represents the noise subspace and consists of the noise eigenvectors, is formed. Finally, the output power spectrum $P(f)$ is computed using the generic vector $a(f)$ as

$$P(f) = \frac{a(f)^H\ a(f)}{||a(f)^H\ E||^2} \ . \tag{4}$$

Theoretically if $f = f_i, i = 1, \cdots, K$, then $a(f_i)$ is orthogonal to the noise subspace, i.e., $||a(f_i)^H E||^2 = 0$, which causes the output response to jump to ∞. In practice, this case results in high peak at $f_i, i = 1, \cdots, K$. Therefore, the output response has K different peaks corresponding to the K different signal components in the reflected signal.

Since R is constructed as in (3), thus it has a unity rank. An averaging algorithm is needed, before employing the eigenvalue decomposition on R, in order to restore its rank. Therefore we apply an averaging algorithm, namely *forward backward averaging method* [4]-[6], to the covariance matrix R (3) and obtain an averaged one, on which we apply the eigenvalue decomposition, as described above.

3. CONCEALED WEAPONS DETECTION SYSTEM

In this section, we describe the complete concealed weapons detection system in details. In addition, we present the block

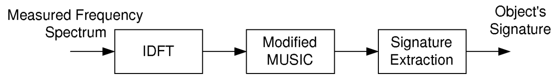

Fig. 3. Block diagram of the detection algorithm.

diagram of the detection approach. Fig. 2 depicts the complete detection system, which consists of a number of sensors as well as a central processing unit. The sensors can be mounted to walls or ceilings forming an interrogation zone. These sensors screen the people in the formed interrogation zone, without the need for any designated choke point. In general, one weapon or more can exist in the interrogation zone. Thus, the detection system first detects if a weapon is present, then classifies what kind of weapon it is. In this paper, we consider that only one weapon exists in the the interrogation zone and we identify it based on its EM signature.

Prior to being deployed, each sensor's memory will be loaded with a library of EM signatures. These unique signatures will be extracted using noise-free measurements of the objects within the Ka-band (26-40 GHz) frequency spectrum. Once a sensor is installed, it continuously uses millimeter-wave (mm-wave) frequencies to excite the EM resonances of the interrogated object. Then, it measures the resulting frequency response. The detection algorithm is then tasked with estimating whether one or more of the signatures within the library are present in the measurement.

Finally, each sensor will send its decisions regularly to the central unit. The central unit collects the local decisions from the sensors and combines them to reach a final decision, whether there exit threatening objects or not. Once a person is identified as carrying a weapon, law enforcement officers will be alerted to intercept the particular individual.

The block diagram of the proposed detection algorithm is shown in Fig. 3. Each sensor measures the response of the reflected signal from the interrogated object at each frequency. Then, the constructed frequency spectrum is fed into the detection system, so that the resonant frequencies can be extracted as follows. First, the input frequency spectrum is converted to a time-domain signal using the standard Inverse Discrete Fourier Transform (IDFT) procedure. Then, the resulting time-domain signal is filtered by a non-linear filter, which corresponds to applying the modified version of the MUSIC algorithm, described in Section 2. Finally, the resonant frequencies, where there exist high peaks, are identified using a conventional peak-detection algorithm. These resonant frequencies represent the object's signature.

4. SIMULATION RESULTS

In this section, we present some computer simulations, which clarify the effect of applying the proposed detection approach on extracting the signature of each interrogated object. We apply our proposed detection approach, shown in Fig. 3, on the measured objects' frequency responses provided by Pharad.

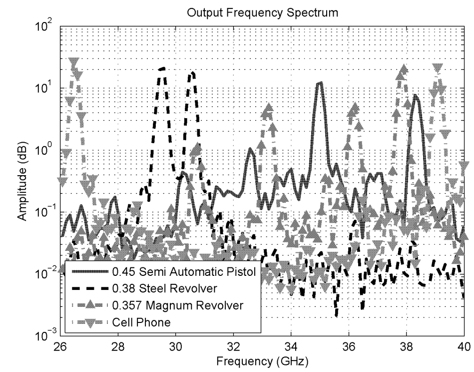

Fig. 4. Frequency spectra of the detection algorithm for various objects.

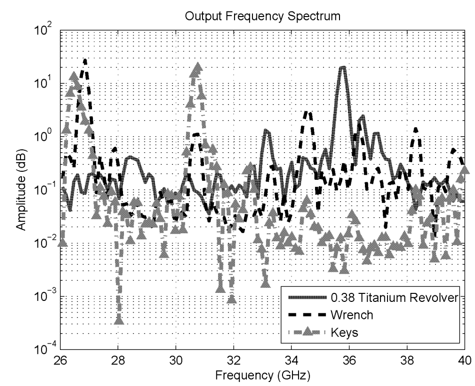

Fig. 5. Frequency spectra of the detection algorithm for various objects.

Pharad uses a mm-wave vector network analyzer (VNA) to provide the mm-wave excitation signals. In addition, the VNA functions as a tunable mm-wave receiver for detecting the returned signals from the target, as well as a data processor in determining the amplitude and phase of each signal.

In Fig. 1, we have shown the measured frequency spectra for various objects and we have illustrated the difficulty of distinguishing these objects based on these measured spectra. Fig. 4 depicts the resulting frequency spectrum of the detection algorithm for the various interrogated objects illustrated in Fig. 1. As shown, the spectrum of each object has more than one peak at certain frequencies, which correspond to the object's resonance frequencies.

In Fig. 5, we show the resulting frequency response for additional interrogated objects, which are the 0.38 titanium revolver, wrench, and a set of keys. Similarly, these objects can be identified using a unique signature for each object. For the interrogated objects shown in Fig. 4 and Fig. 5, we have considered $K = 2$ in the signal model, described in (1). In these figures, each object is characterized by two resonant frequencies, where the highest two peaks occur. Therefore, each object's signature is represented as a two-dimensional vector, representing its resonant frequencies. Consequently, we can

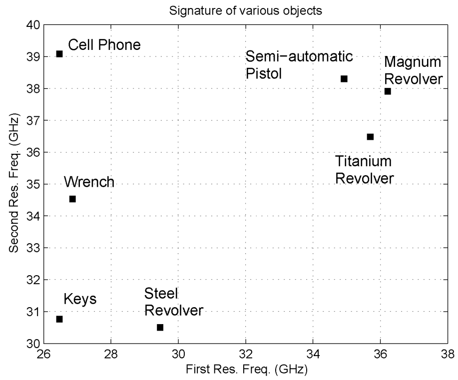

Fig. 6. Two-dimensional signatures of various objects.

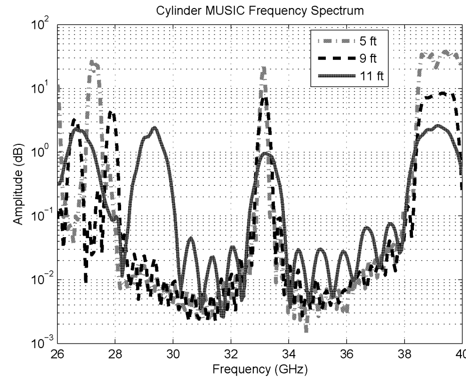

Fig. 7. Cylinder's signature at different distances.

construct a two-dimensional space to represent these objects, where the first and second dimension represent the first and second resonant frequency, respectively.

Fig. 6 depicts the signature of each interrogated object, represented as a point in a two-dimensional plot. As shown, each object has a unique signature, which does not coincide with any other object. In addition, there is a significant gap between the various interrogated objects. More precisely, non-threatening objects such as the cell phone and keys can be easily distinguished from the threatening ones. Having each object of interest represented as a two-dimensional vector allows the classification process of any test object to be implemented very quickly. Furthermore, each sensor needs to store much less information about each object, compared to the matched filter approach [2].

We also consider the dependence of the proposed algorithm on the distance. In order to test that, we have chosen a cylinder that is symmetric with respect to all directions. We have varied the distance between the cylinder and the sensor to be 5, 9, and 11 feet. Fig. 7 depicts the resonance frequencies for the cylinder measured at different ranges. It is shown that there are two major common resonance frequencies among the three different curves, which are $f_1 = 33.14$ and $f_2 = 39.23$. In other words, the cylinder's signature represented as a two-dimensional vector [33.14, 39.23] is independent of the distance between the sensor and the cylinder. Therefore, the response of our proposed algorithm does not depend on the distance between the sensor and the interrogated object, which is one of the main characteristics that should exist in a weapons detection system.

5. CONCLUSION AND FUTURE WORK

In this paper, we have considered the concealed weapons detection problem, where each weapon is identified based on its resonant frequencies. In particular, we have modeled the signal reflected back from any interrogated object as a summation of a number of sinusoidal signals, each corresponds to one of its resonant frequencies. In addition, we have proposed a detection approach, based on a modified version of the MUSIC algorithm, to extract the unique signature of each weapon. We have shown that each interrogated object of interest can be uniquely determined using a two-dimensional vector. Moreover, we have shown that the resonant frequencies, extracted by our proposed detection algorithm, do not depend on the distance between the sensor and the interrogated object.

In future work, different classification algorithms will be proposed to create an alarm indicating the existence of a concealed weapon and further distinguish the different types of weapons. In the situation where an individual may be carrying more than one weapon with multiple weapon spectral signatures being present in the returned signal, some advanced schemes such as neural networks could also be employed to find the boundaries of the target classifications.

6. REFERENCES

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