ANALYSIS OF TERAHERTZ SPECTRAL IMAGES OF EXPLOSIVES AND BIO-AGENTS USING TRAINED NEURAL NETWORKS

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ABSTRACT

A non-invasive means to detect and characterize concealed agents of mass destruction in near real-time with a wide field-of-view is under development. The method employs spatial interferometric imaging of the characteristic transmission or reflection frequency spectrum in the Terahertz range. However, the successful (i.e. low false alarm rate) analysis of such images will depend on correct distinction of the true agent from non-lethal background signals. Neural networks are being trained to successfully distinguish images of explosives and bioagents from images of harmless items. Artificial neural networks are mathematical devices for modeling complex, non-linear relationships. Both multilayer perceptron and radial basis function neural network architectures are used to analyze these spectral images. Positive identifications are generally made, though, neural network performance does deteriorate with reduction in frequency information. Internal tolerances within the identification process can affect the outcome.

Keywords: neural network, Terahertz, interferometry, imaging, multilayer perceptron, radial basis function
1. INTRODUCTION

A growing national security challenge is the development of novel methods to monitor, detect, and characterize hidden lethal agents such as plastic explosives strapped to a person or bioagents in envelopes. The method under study here is based on spatial imaging of the characteristic transmission or reflection wavelength spectrum in the far infrared Terahertz (THz) electro-magnetic radiation range. Artificial neural networks (ANNs) analyses of these THz spectral images are used to distinguish the hidden agents at low false alarm rates from the backgrounds.

Terahertz radiation is attractive for security applications since it typically transmits through plastics, paper products, etc. Either reflective or transmissive THz spectra are claimed for several explosives (1,2) and bioagent simulants and DNA (3). The THz spectra for the explosives appear to be distinguishable from the spectra of human skin and materials such as plastics and cloth.

The interferometric THz detection scheme under development (4) yields spatial images in the 0.2-3 THz range. These images, based on a series of spatial arrays one at each characteristic wavelength, are then processed by trained artificial neural networks (ANNs) in order to achieve positive identification of hidden lethal agents (5). This paper updates our recent progress in ANN processing of the THz images.

2. INTERFEROMETRIC SPECTRAL IMAGING

Constructing images with interferometer arrays is an established technique for astronomical imaging in the radio range (6). Interferometric imaging offers great potential due to its ability to image with only a limited number of detector elements, image many sources of THz radiation at once, image incoherent as well as coherent sources, and provide spectral information as well as spatial imaging data (4).

The imaging interferometer will consist of an array of individual detectors. Signals at two or more points in the aperture plane are brought together to produce cosine and sine (Fourier) components of the brightness distribution. In order to determine a spatial Fourier component and hence the direction of the incoming THz wavefront, the phase delay in the arrival time of the wavefront between a pair of detectors (antennas) must be measured. The relative angle between the direction to the source and the imaginary baseline connecting the two antennas defines the geometric delay $\tau_g$ in arrival of the wavefront between the two antennas. All the directions that form a cone around the baseline have the same phase delay

$$\tau_g = (b \sin \alpha) / c$$

where $b$ is the length of the baseline, $c$ is the speed of light, and $\alpha$ is the relative angle. In order to determine the correct source direction, additional measurements with other orientations of the baseline must be carried out.

For a given number of detectors $N$, there are $N(N-1)/2$ possible pair combinations. An image of the original brightness distribution is generated from the spatial Fourier components of all the different pair combinations by standard Fourier inversion. For efficient coverage of the Fourier Transform u-v plane, it is important to vary the spacing between each detector pair such that each pair produces a unique spatial Fourier component that is not a harmonic of any other component. The spacing is modeled by

$$d_{12} = ar_0 b^{11}$$

where $d$ is the distance from the origin, $a$ is the spacing constant, $r_0$ is the distance of the first detector, and $n$ is the number of the detector. The value $b$ is a constant that describes the rate at which the successive detectors spiral out from the origin. For all the scenarios, it is assumed that data are acquired from the array for every 1° of rotation for a total of 90°. Generation of the image assumes that the distance from the
imaging array to the source is much larger than the typically spacing between the detectors in the array; i.e., far-field planar wavefronts.

Generation of simulated interferometric images begins with the published THz spectra of objects. The objects are placed within a background to simulate an overall problem; e.g., bioagent within an envelope, and a suicide bomber in this paper. The THz radiation incident onto the interferometer corresponds to either the reflection or transmission spectrum of the object(s) being irradiated. The resulting image generation yields two dimensional (spatial) intensity matrices corresponding to fingerprint THz spectral frequencies. The task of the artificial neural network (ANN) is to process these matrices and correctly identify the objects within the problem.

3. NEURAL NETWORKS AND TRAINING

Artificial neural networks (ANNs) are complex mathematical formulations relating (mapping) inputs to outputs (7). In the ANN “training” process, the ANN is presented with a prescribed set of inputs and corresponding outputs. A set of internal parameters (weights) is then optimized so that the outputs predicted by the ANN match the desired outputs to within an acceptable tolerance.

The multilayer perceptron (MLP) is the most common ANN. It consists of input, hidden, and output nodes arranged in layers. The computation at the $k^{th}$ node considers a weighted sum (activation value $net_k$) of inputs (vector $y$). The output, $o_k$, of the node is computed by:

$$ o_k = \tanh(net_k) = \tanh(\sum_{j=1}^{J} w_{kj} y_j + b_k ) $$

(3)

where $w_{kj}$ represents the weights that are optimized during the training process. Bias values $b_k$ are not used here.

A popular alternate ANN architecture – radial basis functions (RBF) – was also applied to the problems in this study. The RBF network contains one hidden layer of basis functions, or neurons. At the input of each neuron, the distance between the neuron center and the input vector is determined. The neuron output is then calculated by applying the basis function (typically Gaussians) to this distance. The RBF network output is a weighted sum of the neuron outputs and a unity bias.

The RBF often contains a linear part. This corresponds to additional direct connections from the inputs to the output neuron. Mathematically, the RBF network, including a linear part, produces an output given by:

$$ \hat{y}(\theta) = g(\theta, x) = \sum_{i=1}^{nb} w_i^2 \exp(-\lambda_i^2 (x_i - w_i^1)^2) + w_{n+1}^2 + \sum_{i=1}^{n} \chi_i x_i$$

(4)

where $nb$ is the number of neurons, each containing a basis function. The parameters of the RBF network consist of the positions of the basis functions $w_i$, the inverse of the width of the basis functions $\lambda_i$, the weights in output sum, and the parameters of the linear part $\chi_1...\chi_n$. The parameters are often lumped together in a common variable $\theta$ to make the notation compact. Then you can use the generic description $g(\theta, x)$ of the neural network model, where $g$ is the network function and $x$ is the input to the network.

The NeuroSolutions® software package from NeuroDimension, Inc.® was used to construct all ANNs in this study. It uses a modular, icon-based network design interface that allows the user to customize networks, generate and compile executable dynamic link library (DLL) files and then embed them into an external, user-supplied interface. The input values (nodes) for ANN training correspond to spectral...
intensities at each frequency. The single output (node) for each material is an arbitrarily chosen integer value.

In this study, trained ANNs in the form of DLLs were integrated into a Labview® interface. The DLL file is an executable module that is called from within the Labview program to perform the mapping from multi-frequency THz spectrum input at a given spatial location (image pixel) to single output value (real number) corresponding to a classification of the material. The Labview program then determines where the value falls within a user-specified neighborhood (tolerance) around each of the integer outputs. A letter is then assigned to the spatial pixel declaring what material is believed to be there. An extension of the Labview program then applies a unique color to each pixel location according to the letter classification. The final color-based spatial image provides for a rapid visual judgment by the user as to the presence of lethal agents, as done in the examples below.

Fig 1: Determinations of contents of envelope using NN analysis - see Table 1 for color code.

MLP Analysis -- all frequencies used

RBF Analysis -- all frequencies used

Fig. 2: Results from NN analysis of bomber problem -- see Table 2 for color code

MLP Analysis -- All frequencies used

RBF Analysis -- All frequencies used

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4. APPLICATION - BIOAGENT IN AN ENVELOPE

The anthrax scare of late 2001 illustrated the vulnerability of our postal system to terrorism. Consider an envelope containing a metal coin, and numerous blotches of organic material including two starch, two flour, and two bacillus subtillus (an anthrax simulant). An examination of published THz transmission spectra for these materials (1,8) resulted in the training set shown in Table 1. The minimum and maximum values of 0 and 10 correspond to total reflection and total transmission, respectively. The desired output are the arbitrary values chosen for classification.

Five interferometric images, each corresponding to one of the five THz frequencies in Table 1, were generated. These spatial intensity matrices were processed, pixel-by-pixel, within the Labview program that accessed the DLL of the trained ANN. Both MLP and RBF architectures were tested. For each pixel, the five-frequency spectrum is analyzed by the DLL, and an output number is produced for comparison to the desired output values for material identification and subsequent color assignment. A fixed absolute tolerance (+/- 0.4) is placed around each desired output value. If the calculated output falls within the neighborhood (tolerance) of a particular desired output, that pixel is assigned the corresponding color. A separate Labview program takes the final matrix of assigned colors and produces the bitmap files presented here.

Table 1: Transmission THz spectral values (refs. 1,8) chosen for ANN training - envelope

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Desired Output</th>
<th>Output Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.073THz</td>
<td>7.52</td>
<td>Red</td>
</tr>
<tr>
<td>0.097THz</td>
<td>2.82</td>
<td>Orange</td>
</tr>
<tr>
<td>0.184THz</td>
<td>3.23</td>
<td>Green</td>
</tr>
<tr>
<td>0.236THz</td>
<td>6.76</td>
<td>Black</td>
</tr>
<tr>
<td>0.290THz</td>
<td>6.47</td>
<td>Blue</td>
</tr>
</tbody>
</table>

The ANN results for the envelope problem are presented via color images in Figure 1. Each object – correctly identified in each case – is visible as a central major-sized color generally surrounded by other color(s). These minor-sized colors correspond to transition zones between the object and the background. The degree of inaccuracies, as evidenced by minor-sized colors, is much reduced with the RBF analysis. The evidence of “unknown” results (i.e. blue) is effectively gone. The improved performance of the RBF is consistent with its preferred capability with “classification” problems (7). Unlike a continuous mathematical function, the identification problems addressed in this study are “classifications.”

5. APPLICATION – SUICIDE BOMBER

The suicide bomber has become the terrorist weapon of choice in some troubled areas of the world. Consider a person with RDX explosive attached to their chest under a shirt (assumed transparent to THz). The bomber also has a metal belt buckle, and some candy (sugar) in their right pocket. An examination of published THz reflection spectra for these materials (1) resulted in the training set shown in Table 2. The minimum and maximum values of 0 and 10 correspond to total transmission and total reflection, respectively. The desired output are the arbitrary values chosen for classification.

Five interferometric reflection images, each corresponding to one of the THz frequencies in Table 2, were generated. These spatial intensity matrices were processed, pixel-by-pixel, within the Labview program that accessed the DLL of the trained ANN. Both MLP and RBF architectures were tested.
Table 2: Reflection THz spectral values chosen for ANN training – AU units – suicide bomber

<table>
<thead>
<tr>
<th></th>
<th>0.03 THz</th>
<th>0.08 THz</th>
<th>0.17 THz</th>
<th>0.26 THz</th>
<th>0.30 THz</th>
<th>Desired Output</th>
<th>Output Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>RDX</td>
<td>3.0</td>
<td>6.8</td>
<td>6.0</td>
<td>2.8</td>
<td>1.6</td>
<td>1</td>
<td>Red</td>
</tr>
<tr>
<td>Skin</td>
<td>3.6</td>
<td>3.1</td>
<td>0.7</td>
<td>1.0</td>
<td>0.2</td>
<td>3</td>
<td>Green</td>
</tr>
<tr>
<td>Candy</td>
<td>2.6</td>
<td>5.4</td>
<td>3.4</td>
<td>2.6</td>
<td>2.4</td>
<td>2</td>
<td>Orange</td>
</tr>
<tr>
<td>Metal</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>4</td>
<td>White</td>
</tr>
<tr>
<td>Off-Person</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>Grey</td>
</tr>
<tr>
<td>Unknown</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Out of range</td>
<td>Blue</td>
</tr>
</tbody>
</table>

The ANN results for the bomber problem using all five frequencies are presented via color bitmaps in Figure 2. The MLP result is poor, with little spatial resolution and nothing correctly identified. The RBF result shows a much-improved spatial resolution. Objects are correctly identified, with slight color inaccuracies in border (edge) transition zones.

6. CONCLUSIONS AND FUTURE WORK

Images of an envelope containing a bioagent and a suicide bomber, generated by simulated multiple frequency (spectral) interferometric imaging, have been analyzed using trained artificial neural networks to identify hidden lethal material and to distinguish it from non-lethal backgrounds. Results suggest that radial basis function networks are generally more accurate than multilayer perceptron networks in this classification-type problem. The lowest frequency spectral image information appears to contribute little to network performance. However, results suggest that removal of additional spectral information will lead to incorrect material identification.

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8. REFERENCES