Neural Network Detection and Identification of Electronic Devices Based on Their Unintended Emissions

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Abstract—**Electromagnetic emissions were measured from several radio receivers to demonstrate the possibility of detecting and identifying these devices based on their unintended emissions. Radiated fields from the different radio receivers have unique characteristics that can be used to identify these devices by analyzing time-frequency plots of measured radiation. A neural network was also developed for automated device detection.**

Keywords-unintended emission; detection; cross-correlation; neural network

I. INTRODUCTION

Electronic circuits often generate radiated electromagnetic emissions that are readily detected [1]. For many electronic devices, reducing emissions even below FCC mandated limits can be a considerable challenge. Electromagnetic compatibility engineers can often recognize the cause of problematic emissions based only on their electromagnetic signature. If emissions from a particular device are properly characterized, they can be used to automatically detect, identify, and locate this device.

Researchers have investigated the possibility of detecting and identifying wireless command-initiated explosive devices based on their unintentional radiated emissions [1-3]. These devices are good candidates for this technique because they are often initiated through inexpensive off-the-shelf wireless receivers that are always actively scanning for a signal from the transmitter. Signals from the receiver's oscillator and other internal electronics easily couple to a device's antenna, connection wires or structure where they are efficiently radiated and may be used to identify its presence. The characteristics of the radiated emissions depend on the characteristics of the receiver, the internal electronics, and the electronic signals within the device. These unique characteristics can be used to detect and identify the device.

The authors are developing methods to detect, locate, and jam wireless command-initiated devices. The methods being used are based on a variety of tools developed by EMC and radio engineers for analysis and testing of electronic products and location of electromagnetic sources. In the following paper, we will discuss preliminary research performed on receivers. The results demonstrate the feasibility of this approach.

II. MEASUREMENT SETUP

The measurement setup shown in Fig. 1 was used to capture the radiated signal and measure the field strength. The devices were put some distance away from the antenna. A biconical antenna was used to measure the unintended radiation from the receiver. The output from the antenna was connected to a pre-amplifier with 23 dB of gain through a 50-ohm coaxial cable. The output of the pre-amplifier was connected to a FM band-stop filter that feeds the Rohde & Schwartz FSEB spectrum analyzer and oscilloscope through 50-ohm coaxial cables.

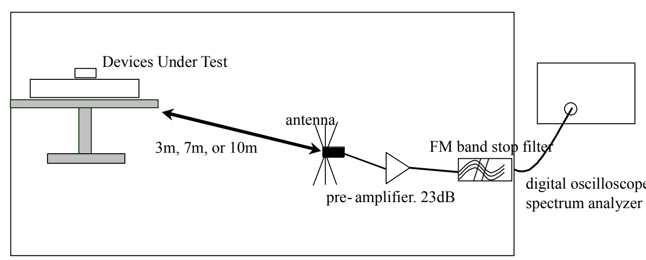

Figure 1. Far field broad band measurement setup

The unintended radiation from radio receivers is relatively low. Background noise from sources like FM radio stations can mask these small signals. To detect the unintended radiation from radio receivers outside the semi-anechoic chamber requires filtering of the ambient noise. To test our ability to detect the receivers in the presence of ambient noise, we first did the measurement in the chamber, then opened the chamber door and repeated the measurements. These experiments were also done in the corridor of our building.

To test the distance from which we could locate the receivers, the devices were put 3m, 5m, 8m, and 10m away from the antenna. The devices tested included two different wireless doorbell receivers and a remote control toy truck. For each environment and each device, more than 40 sample measurements were made. In total 2045 data samples were collected for each device in different environments. The RF data was digitized with a sampling rate of 2.5 Gsa/sec. 20 µs of data was collected for each sample.

III. CHARACTERISTICS ACQUISITION

A. *Unintentional Radiation Pattern of these Devices*

Fig. 2 and Fig. 3 show the time-domain measurements of unintentional radiation from the remote control toy truck. It is an AM modulated signal with a carrier frequency of 49.5 MHz and a modulated envelope frequency of 192 kHz. Fig. 4 shows the spectrum analyzer measurement.

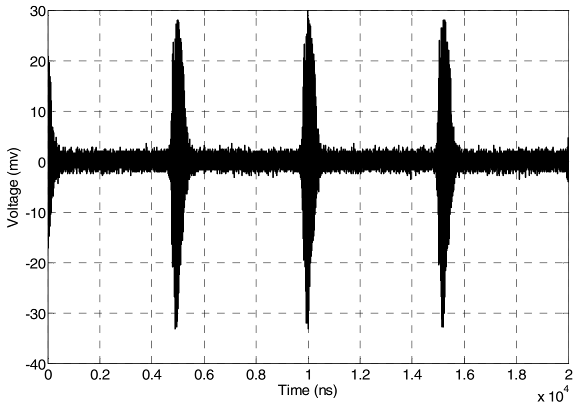

Figure 2. Unintentional radiation from the remote control toy truck (modulated).

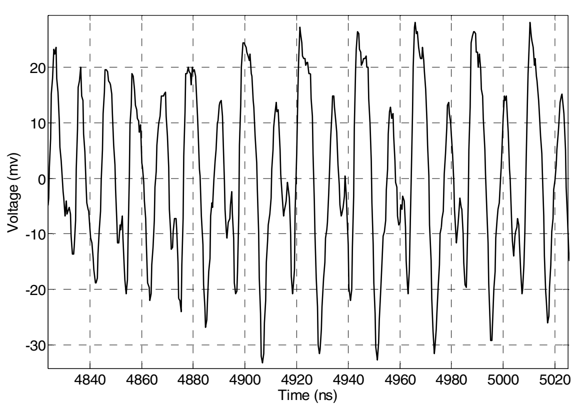

Figure 3. Unintentional radiation from the remote control toy truck (zoomed in).

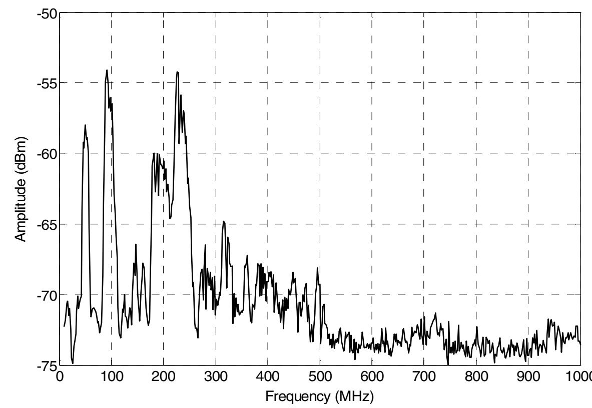

Figure 4. Unintentional radiation from the remote control toy truck (spectrum analyzer measurement).

A similar approach was used to test the other devices measured in this paper. All of these devices exhibit an AM modulation. The modulated envelope frequency and the carrier frequency are listed in TABLE I.

TABLE I. MODULATED WAVE CHARACTERISTICS OF DEVICES

Device Name	Parameters	
	Carrier frequency	***Modulated envelop frequency***
Remote control toy truck	49.5 MHz	0.19 MHz
Door bell 3v	303 MHz	0.44 MHz
Door bell 5v	303 MHz	0.69 MHz

B. *Parameter acquisition*

As mentioned in Section I, the unintended radiation from radio receivers is relatively low. Background noise from sources like FM radio stations can mask these small signals. Fig. 5 shows a time domain measurement of the remote control toy truck when it was 10 m from the antenna in the corridor. The signal was difficult to observe due to the ambient RF noise in the building. The following steps were used to extract signal characteristics from the measurement.

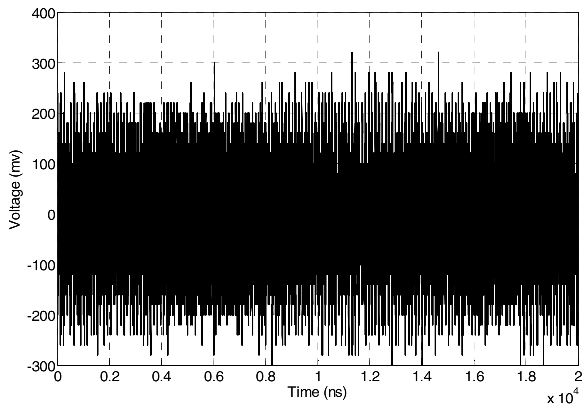

Figure 5. Time domain measurement of remote control toy truck in a noisy enviroment

1) A short-term FFT was performed. Fig. 6 shows a time-frequency domain analysis of radiation from the remote control toy truck 10 m away in a noisy environment.

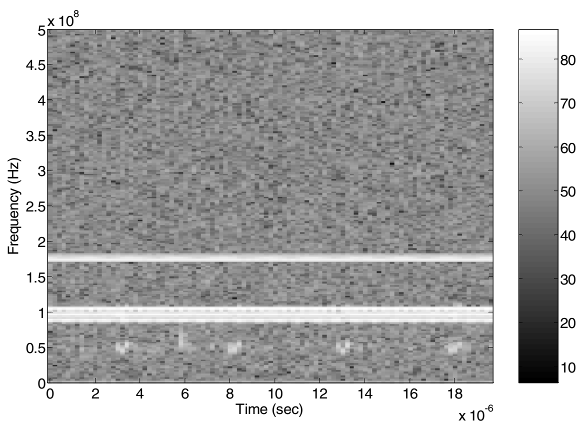

Figure 6. Time-frequency domain analysis of radiation from remote control toy truck in a noisy environment

The bright points around 50 MHz are the signal from the remote control toy truck. The bright lines around 100 MHz are FM radio signals. The bright line around 180 MHz is another ambient noise source.

2) *8 frequency bands were selected.* One band from 42.5 MHz to 57.5 MHz has a very high remote control toy truck signal, another band from 300 MHz to 330 MHz has very high door bell signal. 6 additional frequency bands were randomly chosen, avoiding the FM and other strong ambient noise sources.

3) For each frequency band, the data in that band at each time step was averaged to produce an amplitude vs. time curve. The data was then normalized. Fig. 7 shows the amplitude vs. time curve for the remote control toy truck in the frequency band from 42.5 MHz to 57.5 MHz. In effect, this is the envelope of the measured in-band signal.

A measurement of the same device in the semi-anechoic chamber was performed and processed per steps 1 – 3. Fig. 8 shows the result. Fig. 7 and Fig. 8 have a similar shape but a time shift. Fig. 9 shows the envelope of ambient noise. The shape is quite different from Fig.7 and Fig. 8.

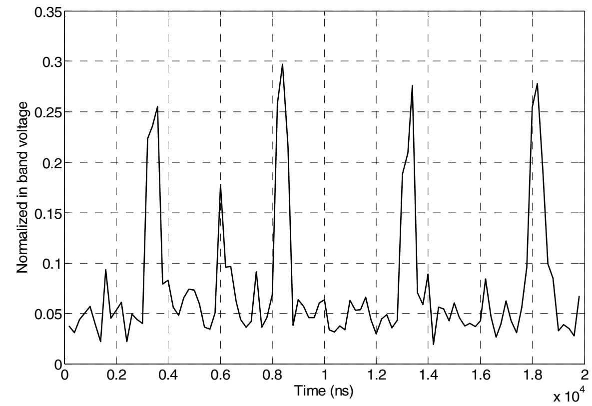

Figure 7. Envelope of the measured in-band signal (10 m away)

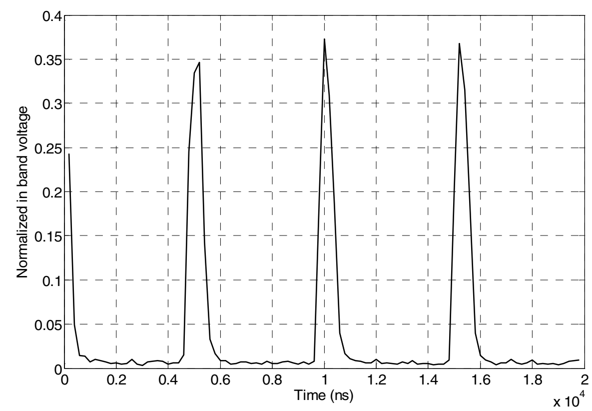

Figure 8. Envelope of the measured in-band signal (in chamber)

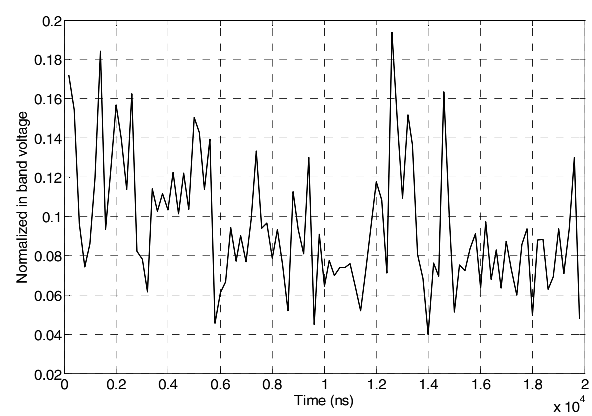

Figure 9. Envelope of the measured in-band signal (ambient noise)

4) To help detect each device, measurements were cross-correlated with data obtained in the semi-anechoic chamber.

The solid curve in Fig. 10 shows the cross-correlation result between the 2045 samples and the measurement of the remote control toy truck in a noise-free environment. The selected frequency band is from 42.5 MHz to 57.5 MHz. The dashed curve shows the measurement environment. There are six different environments as listed in TABLE II. The higher the environment index is, the easier it is to detect the device. A cross correlation result that is higher than the environment index indicates the presence of the device in that environment. In Figure 10, the sample measurements with a cross correlation value greater than 4 indicate the presence of the remote control toy truck with 100% accuracy.

TABLE II. ENVIRONMENT DEFINITIONS

Environment Index	Environments Description
0	No device present
1	The device is set 10m away from the antenna in the corridor
2	The device is set 8m away from the antenna in the corridor
3	The device is set 5m away from the antenna in the corridor
4	The device is set 3m away from the antenna in the corridor..
5	The device is set 3m away from the antenna in the chamber with door open
6	The device is set 3m away from the antenna in the corridor with door closed.

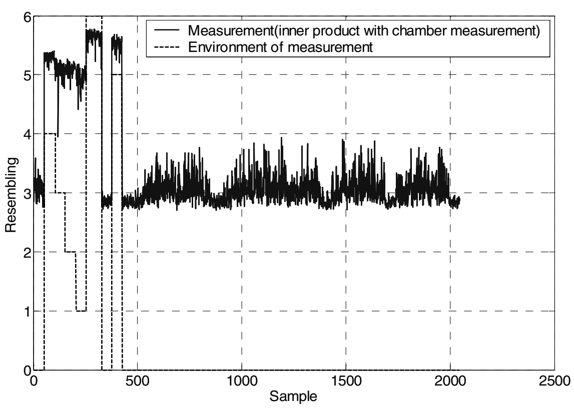

Figure 10. Result of cross-correlating 2045 samples with the clean signal

For the other devices, a similar process can be applied. The probability of detection is not as high as the remote control toy truck because their signals are weaker. For example, Fig. 11 shows the probability detecting a wireless doorbell vs. the probability of making a false detection. Using the previously described technique alone, there is no threshold value that will yield a 100% probability of detection and a zero probability of a false alarm.

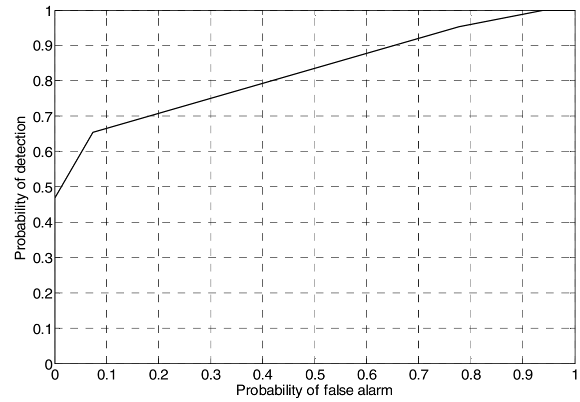

Figure 11. Receiver-operator characteristic of a wireless doorbell

IV. DEVICE DETECTION

As shown in the previous section, this short-term FFT combined with a cross correlation technique can identify different devices reasonably well. However, the error rate is a little high when the device is far away. Artificial neural networks have an ability to recognize complex patterns in the data that may not be obvious to human observers. In this section, we demonstrate how a neural network is used to identify a particular device.

A. *Parameters feeding the neural network*

Data was collected from the three different signal sources, the remote control toy truck and two door bells, and preprocessed using the procedures described in Section III. This data was used as the input for a neural network. For each sample measurement, the data presented to the neural network was the 8 cross-correlation values (i.e. one for each of the 8 frequency bands).

B. *Neural network setup and the training*

There were 2045 measurements from all these devices. Three neural networks were set up to identify the presence or absence of each of the Three different devices. The data was normalized before being presented to the neural network. A multilayer perceptron (MLP) architecture 5S-1L was chosen for the neural networks. The first hidden layer had 5 neurons with a bipolar sigmoid transfer function. A linear transfer function (L in the notation) was used in the output layer, which has 1 neuron. The output neuron was used to identify if the device was present or not.

In the training of each neural network, half of the 2045 measurements were used for the training, a quarter of the data points were set aside as the validation set and a quarter were reserved for the final test. The Levenberg-Marquardt algorithm was used to train the neural networks.

C. Experimental results

Upon completion of the training, the neural networks were assessed using the reserved test set, based on two terms. One term was the signal identification rate, which is the number of correctly identified signals divided by the total number of the signals in the test set. The other was the noise identification rate, which is the number of the correctly identified noise (or lack of a signal) measurements divided by the total number of the noise measurements in the test set. Since the training of the neural network started with random weight matrices, to summarize the statistical properties of the device identification results, each neural network was trained from 50 different random weight matrices. The mean and the standard deviation of signal and noise identification rates are presented in Table III. The neural networks identified the different devices, especially on the remote control toy truck, with a high degree of accuracy. Interestingly, the noise identification rate was extremely high, which is particularly important in real applications.

TABLE III. SIGNAL AND NOISE IDENTIFICATION RATE BY THE NEURAL NETWORK

Device Name	**Device Identification Rate**			
	Mean_signal	***Std_signal***	***Mean_noise***	***Std_noise***
Remote control toy truck	100%	0%	100%	0%
Door bell 3v	98.58%	0.58%	99.92%	0.12%
Door bell 5v	98.39%	0.86%	99.90%	0.13%

V. CONCLUSIONS

All active electronic devices radiate some electromagnetic energy, either intentionally or unintentionally. These emissions can be used to detect and locate these devices. Using a variety of low-cost wireless receivers, we have demonstrated the potential to detect and identify these receivers based on their unintentional radiated emissions using neural networks. Good results were achieved even in a very noisy environment.

REFERENCES

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