Detection and Identification of Vehicles Based on Their Unintended Electromagnetic Emissions

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Abstract—When running, vehicles with internal combustion engines radiate electromagnetic emissions that are characteristic of the vehicle. Emissions depend on the electronics, harness wiring, body type, and many other features. Since emissions are unique to each vehicle, these may be used for identification purposes. This paper investigates a procedure for detecting and identifying vehicles based on their RF emissions. Parameters like the average magnitude or standard deviation of magnitude within a frequency band were extracted from measured emission data. These parameters were used as inputs to an artificial neural network (ANN) that was trained to identify the vehicle that produced the emissions. The approach was tested using the emissions captured from a Toyota Tundra, a GM Cadillac, a Ford Windstar, and ambient noise. The ANN was able to classify the source of signals with 99% accuracy when using emissions that captured an ignition spark event.

Index Terms—Detectors, electromagnetic radiation, identification, neural networks, vehicles.

I. INTRODUCTION

MODERN vehicles utilize a large array of electronic devices. Their electrical systems are becoming increasingly complex, as they are composed of microprocessor circuits, power delivery networks, safety control circuits, communication circuits, entertainment devices, sensors, motors, electronic ignitions, and more. Hundreds of wires are used to route electrical signals from these devices through the vehicle. These signals, when coupled to an appropriate antenna, can cause significant intentional or unintentional electromagnetic radiation [1], [2].

The characteristics of the electromagnetic emissions from a vehicle depend on harness routing, vehicle geometry, and the signals produced by the vehicle's electronic components. As these parameters vary greatly among vehicles, two vehicles with different electrical systems will generally produce different electromagnetic emissions. These emissions may be unique to
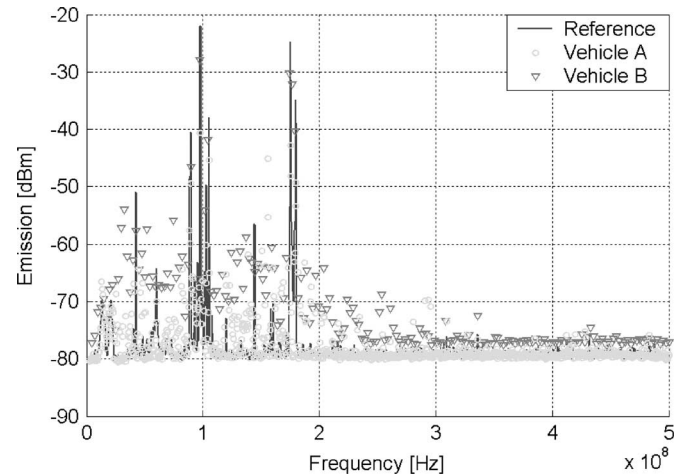
Fig. 1. Emissions spectra from different automobiles.

each vehicle. Several different techniques can be applied to process the electromagnetic emissions in a form that highlights the differences in emissions among vehicles, including time-domain waveform analysis, spectrum analysis, short-term FFTs, zero-span measurements, AM/FM demodulation, and others [3], [4]. Researchers have previously investigated the possibility of detecting, locating, and identifying electronic devices based on their electromagnetic emissions [3]–[8]. In all of these studies, the radiating sources are relatively simple. The radiation pattern from a vehicle can be very complicated because the vehicle utilizes many electronic devices and the radiation is a function of all of these devices and the vehicle geometry. However, if emissions from a particular vehicle are properly characterized, they might be used to detect, identify, and locate this vehicle automatically.

Fig. 1 shows the emissions spectra from two different vehicles compared with the ambient fields in the Automotive Electromagnetic Compatibility (EMC) Laboratory at the University of Missouri–Rolla (UMR). The emissions were measured using a biconical antenna connected to a spectrum analyzer, set to a resolution bandwidth of 100 kHz and maximum hold. The figure shows that the spectrum varies significantly from one automobile to another. Additional differences are seen in the time domain. These differences might be used to automatically detect and identify vehicles based on their electromagnetic emissions.

Artificial neural networks (ANNs) are widely used in automatic target recognition and pattern identification and classification problems [8]–[15]. The ANN is a powerful, robust,

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│  Measure emissions from automobiles     │
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│  Apply short-term Fourier transform to  │
│  the measured emission data             │
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│  Extract parameters from spectrograms   │
│  of emissions                           │
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│  Preprocess parameters so that the mean │
│  is 0 and the standard deviation is 1   │
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│  Reduce data set by applying principal  │
│  component analysis. Get the transfer   │
│  matrix                                 │
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│  Train and test the ANN with the        │
│  reduced dataset                        │
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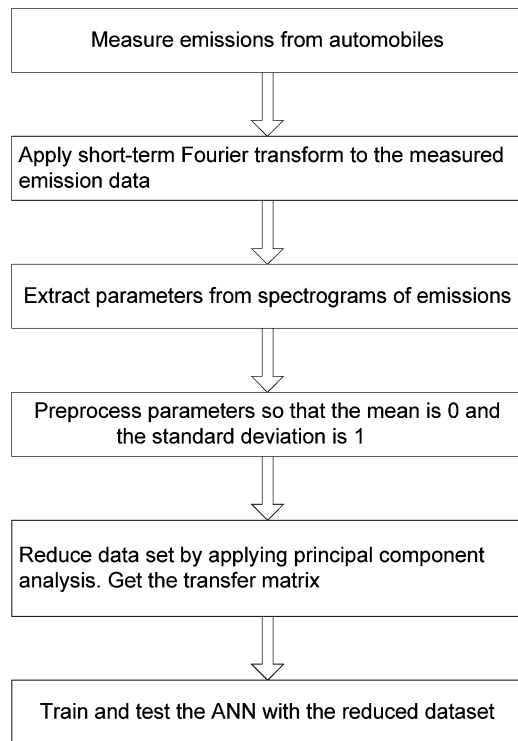
Fig. 2.   Procedure used to test and train the ANN and extract parameters.

and adaptive method for detecting and classifying targets with changing properties that operate in a changing environment [16]. It has the capability to learn and generalize from training sets to similar but new data not included in the training set. With appropriate training, it can automatically extract salient characteristics of the data and classify samples efficiently.

This paper presents an approach to detect and identify vehicles based on their unintentional electromagnetic emissions. Detection and identification were performed using an ANN. The network was trained and tested using emission data measured from several vehicles, as well as emission data for the ambient noise. The ANN used the parameters extracted from the measured emissions that were indicative of the vehicles, rather than using the raw measurements themselves. It was able to successfully identify the vehicle responsible for the emissions using this data.

II. METHODS

The process used to evaluate the capability of an ANN to identify vehicles based on their unintentional emissions is illustrated in Fig. 2. The measured emission data were first processed by applying a short-term Fourier transform (STFT) to the data to obtain a time–frequency spectrogram. The number of parameters in the spectrogram is too big to feed to the neural network by itself. To reduce the data fed to the neural network, several parameters were extracted from the spectrogram that focus on specific characteristics of the signal. The data fed to the neural network were then further reduced by applying principal components analysis (PCA) to the parameter matrix. The resulting components were used to test and train the neural network. Each

of the steps involved in this process is explained in detail in the following sections.

A. Measured Emissions

Radiated electromagnetic emissions were measured from a General Motors Cadillac sedan, a Ford Windstar minivan, and a Toyota Tundra pickup truck. Emissions were measured using a biconical antenna connected to a sampling oscilloscope. Time-domain signals were sampled at a rate of 500E+06 samples per second for 100 μs and saved to a disk for later processing. Measurements were performed either in the UMR Automotive EMC Laboratory or outside in an open-air environment. Neither location was shielded, so the measurements included significant ambient noise. Emissions capturing a spark event were measured over five days for a total of 843 measurements. The number of measurements was roughly equal among vehicles and among days. Measurements of ambient noise were measured over seven days (both inside and outside the laboratory) for a total of 326 measurements.

B. Pre-processing of Data

Fig. 3 shows examples of the time- and frequency-domain emissions from the vehicles and of the ambient noise. The pulses in the time-domain plots are due to the firing of the spark plug (the ignition pulse). From these plots, it is difficult to tell the difference between the two vehicles or even the difference between vehicles and ambient noise for the frequency-domain plots. However, differentiation may be achieved by combining the time- and frequency-domain information.

1) Short-Term Fourier Transform: Time–frequency analysis shows how the frequency content of a signal changes over time. This description is especially important when the signal contains short-duration events, where it may be difficult to distinguish characteristics in the time- or frequency-domain alone. Many distributions may be used for time–frequency analysis, for example, the Wigner distribution, windowed Wigner distribution, sinc distribution, STFT or spectrogram, and wavelet, among others [17]. Here, we use the STFT.

Fig. 4 shows an example of STFT spectrograms of the automobile emissions and of the ambient noise. The frequency content is shown from 0 to 250 MHz as a function of time from 0 to 100 μs. A 60-point window size was used to generate the STFT. No additional filtering was performed. The three horizontal lines near 100 MHz are FM radio stations. The white bands near 70 and 130 MHz are due to unidentified intermittent noise sources. These bands appear in some measurements but not all. Faint horizontal lines at other frequencies are also due to unidentified noise sources. The vertical streak appearing in measurements of the automobile are due to the ignition pulse. Differences among the vehicle emissions are much clearer in the STFT spectrograms than in the time- or frequency-domain plots. Several automobiles were evaluated and the spectrum and duration of the ignition pulse varied significantly from one automobile to another. While one can see differences in the background of these plots, much of this difference is due to the changes in the ambient noise. The ambient noise varied significantly from
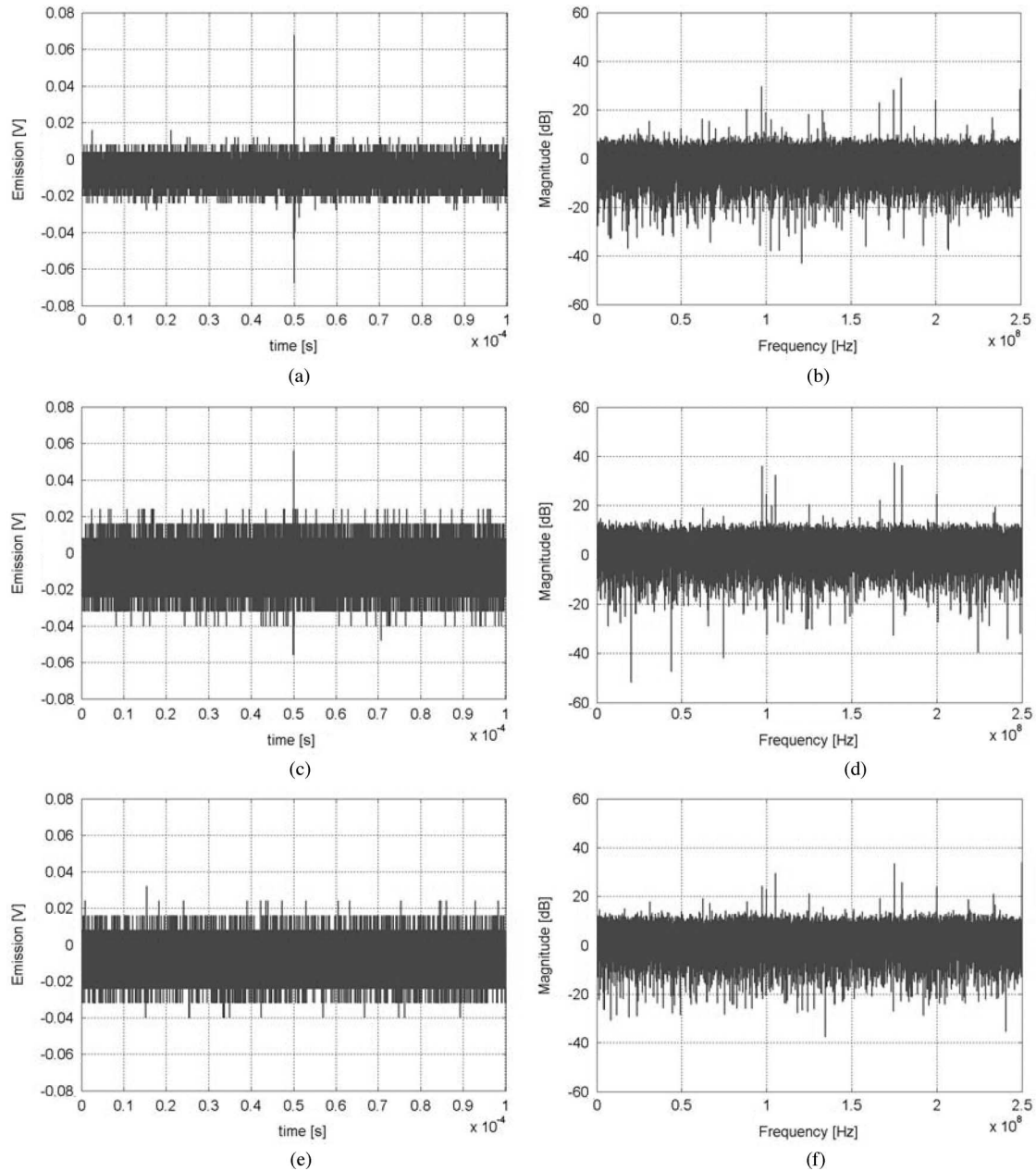
Fig. 3. Example of emissions from vehicles and of ambient noise. (a) Time-domain emissions from vehicle A. (b) FFT of (a). (c) Time-domain emissions from vehicle B. (d) FFT of (c). (e) Time-domain ambient noise. (f) FFT of (e).

one measurement to another. For example, the ambient noise measurement shown in Fig. 4(c) includes a narrow-band signal around 70 MHz. This narrow-band signal appeared only in some of our ambient measurements.

2) Parameter Extraction: The emission spectrograms contain too much information to be fed in raw form to a practical neural network. To reduce the number of input variables, five groups of parameters were extracted from STFT plots. Each parameter targeted different characteristics of the emissions. These parameters were calculated for DC and for 30 8.33-MHz frequency bands to 250 MHz, giving a total of $5 \times 31 = 155$ parameters. The parameters were as follows.

1) *Maximum spectral magnitude over a frequency band (e.g., from 0 to 8.33 MHz) divided by the average magnitude over the frequency band*: This parameter helps distinguish between pulses and pure-tone signals and provides some information about the size of the pulse. For a long-duration pure-tone signal, the maximum over the average value would be close to one for the frequency band of interest. A short-duration pulse would give a much larger value. A wide-band pulse would give a large value over several frequency bands.

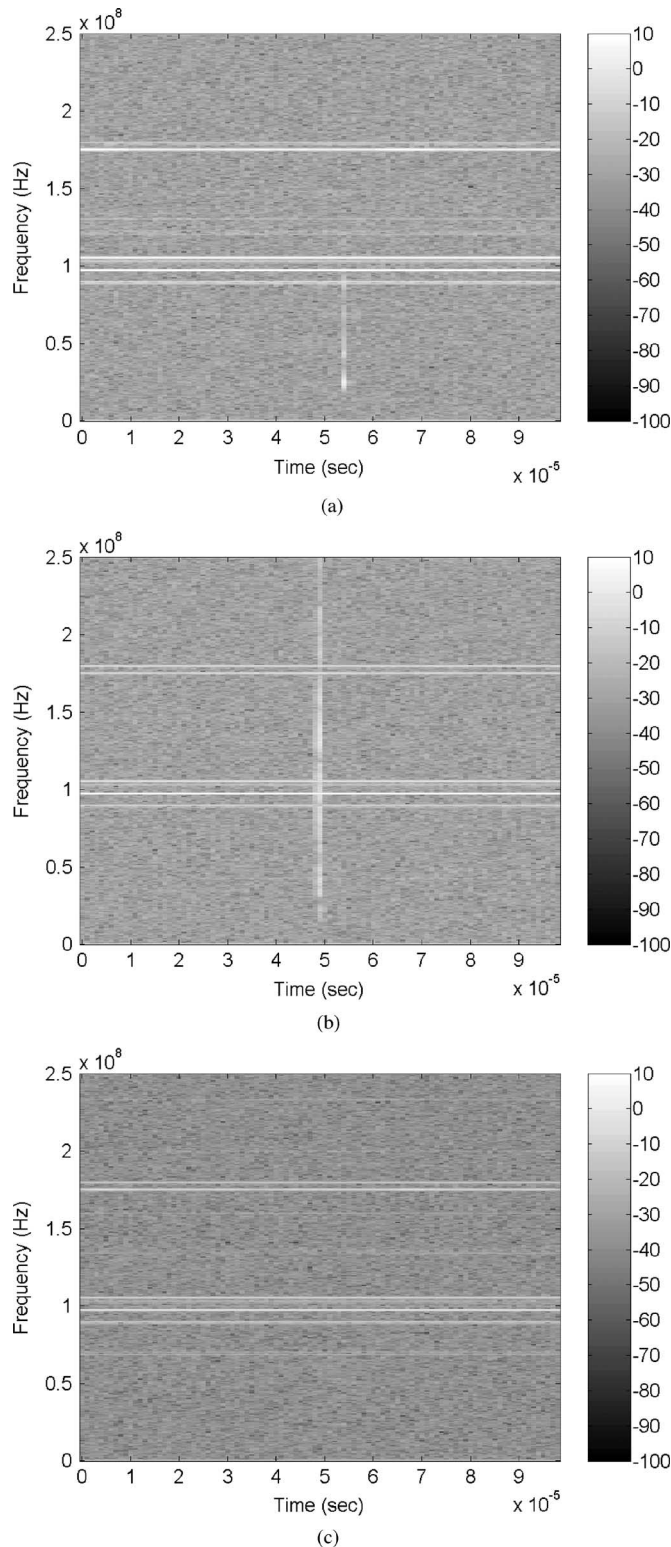2) *Average magnitude over a frequency band divided by the average magnitude over the entire time–frequency plot*

Fig. 4. Spectrogram of ambient noise and of emissions from different automobiles when a spark event was captured. (a) Emissions from vehicle "A" during a spark event. (b) Emissions from vehicle "B" during a spark event. (c) Ambient noise (reference).

(i.e., all frequency bands): This parameter indicates the relative activity within a particular frequency band. It would take on a large value over frequency bands with a long-duration pure-tone signal or many short-duration

pulses. The value would be small for a short-duration pulse or noise.

3) *Standard deviation of magnitude over a frequency band*: A long-duration pure-tone signal would give a small value for this parameter. Many short-duration pulses would result in a large value, for example, as a result of radiation from a clocked digital component within the vehicle. Similarly, a strong wide-band pulse would give a relatively large value over many frequency bands. This parameter could have a large value in the presence of high-amplitude random noise.

4) *Number of points within 3 dB of the maximum spectral magnitude within a frequency band*: This parameter helps differentiate sharp, fast pulses from other signals. It generally has a small value for a fast pulse, a relatively large value for a pure-tone signal or random noise, and a value somewhere in between for a slow pulse.

5) *Number of pulses within a frequency band*: This parameter may be useful for differentiating between a spark event and pulses caused by other activities in the vehicle. A single pulse is defined from the time the magnitude comes within 3 dB of the maximum magnitude over the frequency band to the time the magnitude drops below the average magnitude over that band. A long-duration pure-tone signal would produce a small value. A single strong pulse would produce a value of 1. Periodic digital activity would yield an intermediate value. Random noise alone would generally yield a large value.

3) Principal Component Analysis: While the amount of data was reduced significantly by extracting the parameters defined above, the number of parameters is still too large, especially for adequate training using a reasonable sized dataset. The number of inputs to the neural network was further reduced using PCA. PCA compresses a dataset by transforming a number of correlated parameters into a smaller number of uncorrelated parameters called principal components [18].

PCA assumes the input data set has been normalized so that it has a zero mean. Normalization was done using the equation

$$X_n = \frac{X - \mu_X}{\sigma_X} \qquad (1)$$

where X_n is the normalize data set, X is the sampled data set for each variable, μ_X is the mean of the of the sample set, and σ_X is the standard deviation. After normalization, the data set will have a mean of 0 and standard deviation of 1. The data set obtained from PCA was used to train and test the neural network.

C. Neural Network

Numerous neural networks are available for pattern identification. A multilayer perceptron (MLP) feed-forward neural network trained with back propagation (BP) was chosen to analyze the data because it has many properties useful for the vehicle identification problem. It can efficiently learn large data sets, it has been shown to be effective for pattern recognition

problems, it can be related to the Kalman filter, and it has many other useful characteristics.

The specific parameters of the neural network used in our work, like the number of input neurons, were varied depending on the input data, as shown in Section III. The neural network was trained using the PCA data outlined above. The mean and standard deviation and the principal component transformation matrix were determined from the training data. This information was used to process both the training and the test data for the neural network.

III. RESULTS

A. Detection and Identification Results

Measured emissions that caught an ignition spark event were used to test and train the neural network. Measured emissions were separated into testing and training data. The neural network was trained using data measured on the first four days (824 measurements) and tested using data measured on the fifth day (286 measurements). Devices under test included the GM Cadillac, Ford Windstar, and Toyota Tundra, as well as reference measurements (i.e., ambient noise with no vehicle present). All five parameters described in the previous section were used by the neural network. PCA reduced the number of inputs for a single measurement from 155 parameters to 10. The neural network used ten input neurons, two hidden layers of five and four neurons, respectively, and a four-neuron output layer. A hyperbolic tangent sigmoid transfer function was used for the input and hidden layers and a linear transfer function was used for the output layer. The network produced a four-element vector, with each element taking a value between 0 and 1. After normalization, the value of each element roughly indicates the probability that the input is a particular vehicle or ambient noise. The neural network was trained until it reached a mean-square error (MSE) of 1.0×10^{-5} or for 10 000 training epochs, whichever came first. In most of the cases, the training reached the MSE goal. After training, the network was applied to the test data. Using this approach, the neural network was able to correctly identify 99.3% of the measurements in the test data (284 measurements were identified correctly and two were not).

B. Data Analysis

The five parameters used to identify the vehicle target different characteristics of the measured emissions. To show the importance of each parameter, attempts were made to identify the emissions using fewer parameters. The results are summarized in Table I.

Results indicate that parameters 1 (maximum over average), 4 (number of points within 3 dB of the maximum), and 5 (number of pulses) provide the most information about the identity of the vehicle. This result is not surprising as this experiment depended on the capture of an ignition pulse and parameters 1, 4, and 5 are more sensitive to wide-band, short-duration pulses than are parameters 2 (average over band divided by average over plot) and 3 (standard deviation). However, parameter 3, in particular, appears to add additional information that is not available from

TABLE I
ABILITY TO IDENTIFY VEHICLES USING SUBSETS OF
THE AVAILABLE PARAMETERS

Parameters used	# parameters after PCA	Number of perceptrons on every layer of ANN	Hit rate
1,2,3,4,5	10	10-5-3-4	99.3% (284/286)
2,3,4,5	10	9-5-3-4	95.5% (273/286)
1,3,4,5	8	8-5-3-4	99.7% (285/286)
1,2,4,5	10	10-5-3-4	90.6% (259/286)
1,2,3,5	8	8-5-3-4	99.0% (283/286)
1,2,3,4	10	10-5-3-4	98.3% (281/286)
2,4,5	9	9-5-3-4	98.3% (281/286)
3,4,5	9	9-5-3-4	100% (286/286)
2,3,5	8	8-5-3-4	98.3% (281/286)
2,3,4	8	8-5-3-4	88.8% (254/286)
1,4,5	10	10-5-3-4	96.2% (275/286)
1,3,5	8	8-5-3-4	99.7% (285/286)
1,3,4	8	8-5-3-4	98.6% (282/286)
1,2,5	10	10-5-3-4	87.8% (251/286)
1,2,4	9	9-5-3-4	85.0% (243/286)
1,2,3	9	9-5-3-4	89.9% (257/286)
1,2	10	10-5-3-4	88.8% (254/286)
1,3	7	7-5-3-4	83.6% (239/286)
1,4	10	10-5-3-4	95.8% (274/286)
1,5	8	8-5-3-4	99.0% (283/286)
2,3	8	8-5-3-4	51.7% (148/286)
2,4	11	11-5-3-4	82.5% (236/286)
2,5	10	10-5-3-4	88.8% (254/286)
3,4	9	9-5-3-4	98.3% (281/286)
3,5	6	6-5-3-4	99.3% (284/286)
4,5	12	12-5-3-4	96.9% (277/286)
1	9	9-5-3-4	91.6% (262/286)
2	8	8-5-3-4	42.3% (121/286)
3	3	3-5-3-4	75.5% (216/286)
4	13	13-5-3-4	91.3% (261/286)
5	13	13-5-3-4	93.4% (267/286)

parameters 1, 4, and 5. Results improved when parameter 3 was used along with the other parameters. For example, the combination of parameters 1–4–5 did not yield results as good as did the combinations 3–4–5, 1–3–5, 1–3–4, or 1–3–4–5. Parameter 2, on the other hand, appears to contain little useful information and often reduced the overall effectiveness of the neural network. The best single parameter was parameter 5, the number of pulses within a band. Parameters 3 and 5 together were capable of identifying 99.3% of the vehicles in the test set.

IV. DISCUSSION

Since neural networks were able to identify vehicles from their electromagnetic signature, an important question is whether the identification is straightforward and could be obtained with simpler methods, for example, using a simple threshold technique. To investigate this question, the statistical characteristics of the measured data were analyzed. Fig. 5 shows a box and whisker plot of one principal component after PCA when all five groups of parameters were used to identify the vehicle. The line in the middle of each box shows the median value of the data. Boxes extend above and below the median to include 25% of the measured data in each direction. Whiskers extend to the minimum and maximum values. The "+" marks indicate statistical outliers outside the expected range of values. For most parameters, there were no clear thresholds that would allow identification of a particular vehicle. The principal component in Fig. 5 gave greater separation among vehicles than any other component, but no range of thresholds would allow definitive identification of any one vehicle, particularly
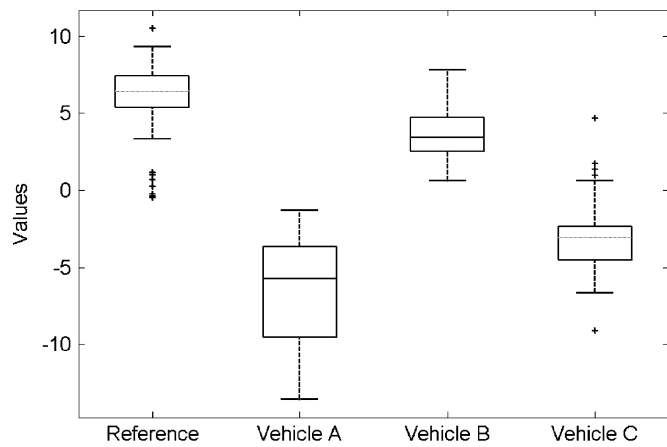
Fig. 5. Box plot of one principal component when all five groups of parameters were used to identify the vehicle.

with 98% accuracy. A more sophisticated combination of components is needed, as was implemented by the neural network.

While the results show it is possible to identify a vehicle when an ignition pulse is captured, it may also be possible to identify the vehicle without using the ignition pulse. A vehicle emits radiation from many sources that are unrelated to the ignition pulse, though the ignition pulse is one of the strongest sources. To test the possibility of identifying vehicles without the ignition pulse, emissions that did not capture an ignition pulse were measured over the course of one day while the vehicle was running (94 measurements of emissions and ambient noise). Fig. 6 shows an example of these ambient and emission measurements. It is difficult to distinguish among these plots by the naked eye. When we attempted to identify the vehicles without using the ignition pulse, we were unsuccessful. A significant problem with our test was that emission measurements were made in an unshielded environment. As there was significant ambient noise in our measurements, a weak signal could easily be missed in our analysis. If measurements of vehicle emissions could be made in a "noise-free" semi-anechoic chamber, processing techniques could be created that extract weak emissions even from significant noise, thus allowing identification without an ignition pulse. Preliminary studies of other emissions sources in our laboratory have successfully demonstrated this possibility. If identification must rely on capturing an ignition pulse, one must take special precautions to ensure an ignition pulse is captured during the measurement process. In our tests, measurements were taken over 100 μs. As an ignition pulse occurs on the order of every tens of milliseconds, the 100-μs window must be triggered carefully.

A possible reason we were unable to identify a vehicle without the ignition pulse may be that the parameters we used were inappropriate for the task. Most of the parameters focused on pulses or narrow-band, long-duration signals. Emissions from other sources in the vehicle may not fit this model well. It may be possible to improve the performance of the neural network by developing parameters that focus on other emission sources or parameters that rely on a template library (for example, a
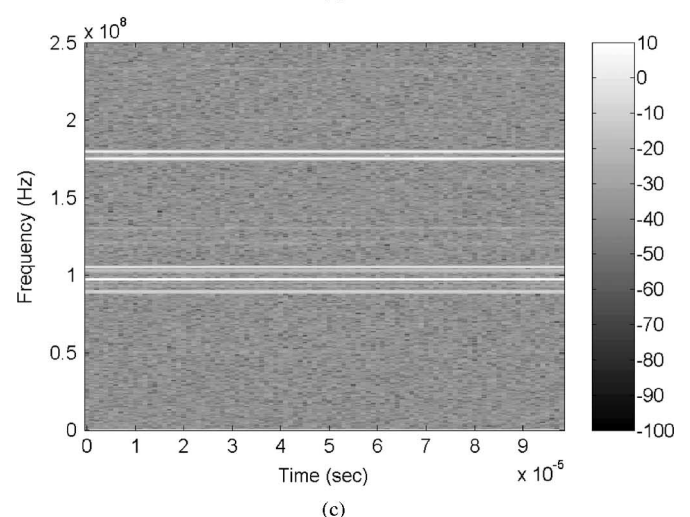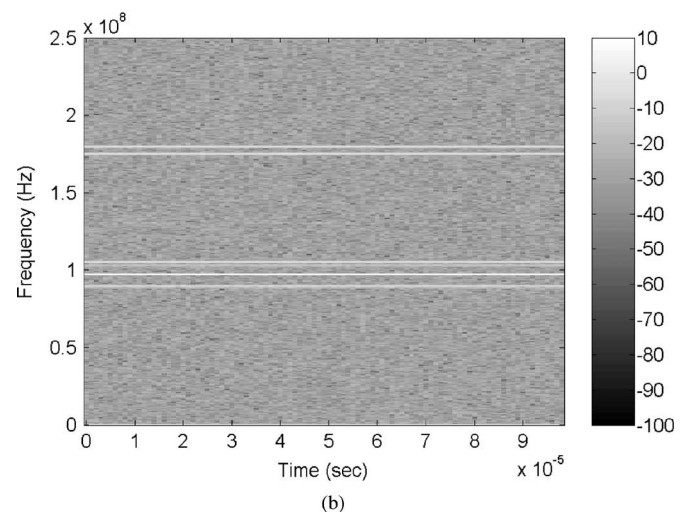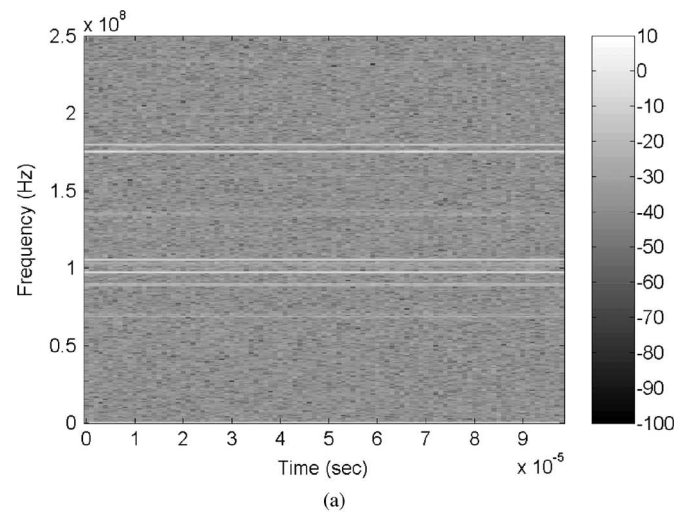

(a)

(b)

(c)

Fig. 6. Spectrograms of ambient noise and of emissions from different automobiles when no ignition event was captured. (a) Emissions from vehicle "A" when a spark was not captured. (b) Emissions from vehicle "B" when a spark was not captured. (c) Ambient noise.

cross-correlation with a reference measurement) or by using more sophisticated neural network architectures.

Automobiles were automatically identified in this paper using ANNs. Another approach may be to use a "man-in-the-loop."

The human brain is a powerful signal processing engine. By down sampling high-frequency emission measurements to audio frequencies, one can listen to emissions. With proper training, one might be able to identify the vehicles based on these sounds. Preliminary results show that different vehicles do sound different when their RF signals are converted to acoustic signals. A similar approach has been used to identify sources of emissions from electronic products in the UMR EMC Laboratory.

In this paper, a system was developed to identify vehicles based on their unintentional emissions. The system was tested in the laboratory and can successfully identify three vehicles and ambient noise. Before this method can be used in the real world to identify a wide variety of vehicles at a distance in a noisy environment, however, several problems and open questions must be addressed.

One problem that must be addressed is the signal-to-noise ratio. In this paper, the emissions from vehicles were measured with an antenna placed close to the vehicle—about 1–3 m. The close proximity was partly due to space limitations. However, the signal will drop significantly and may be overwhelmed by the ambient noise when the vehicle is far away from the antenna or if the vehicle was in the presence of significant ambient noise, as might occur at an airport or military base. Pre-amplifying signals from the antenna, using directional antennas, filtering, and applying other signal processing techniques would all help to improve the signal-to-noise ratio. Pre-amplifying and filtering signals are especially important when capturing data on an oscilloscope with only 6–8 bits of dynamic range, which complicates measurement of signals more than 46 dB below the strongest source (for example, an FM radio station).

An important open question is the variation of emissions characteristics among automobiles of the same make, among vehicles from the same manufacturer, or for a specific vehicle over time. For identification, it is desirable that a specific vehicle make has relatively predictable emissions over time but that there be considerable variation among different vehicle models or manufacturers. Experiments are needed to show the significance of these variations beyond the vehicles studied here.

V. CONCLUSION

An approach to detect and identify vehicles based on their electromagnetic emissions was presented. Identification was enabled using neural networks. Several parameters were extracted from spectrograms of the measured emissions to highlight differences among vehicles and ambient noise. The standard deviation and number of pulses within a frequency band were the most important parameters. Using those two parameters alone when a spark event was captured, an identification rate of 99.3% could be achieved. When a spark event was not captured, however, the neural network was unable to successfully identify the responsible vehicle. It is possible that detection of vehicles without using the ignition pulse could be accomplished if "noise-free" measurements of the vehicle were available to better train the network and to help form more useful parameters that characterize the vehicles in this case.

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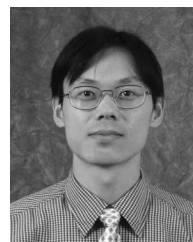
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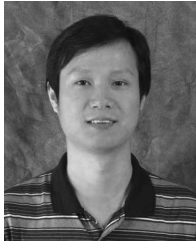
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Michael Noll, photograph and biography not available at the time of publication.

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