Acoustical Signal Processing for Classifying and Tracking Ground Vehicles

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Sensor networks with embedded processing and wireless communication nodes play a critical role in improving situational awareness on the modern battlefield and for surveillance operations. Aeroacoustic and seismic sensors are particularly attractive because they are rapidly-deployable and low-cost, so they may be used to monitor large areas as well as choke points where traffic is high [1].

The data collected by a network of aeroacoustic and seismic sensors may be processed to localize the positions of ground vehicles, track the vehicles as they move, and identify the type of vehicle. The localization, tracking, and identification algorithms typically operate in parallel and with minimal sharing of information. The performance of the localization, tracking, and identification algorithms can be improved with additional information sharing and signal processing. Examples of information sharing include predicted source locations (from the tracking algorithm to aid the localization algorithm), differential Doppler (from the sensor nodes to aid data association in the tracking algorithm), and source aspect angle, range, and velocity (from the tracking algorithm to aid identification based on features from nodes).

Our focus in this summary is on the problem of identifying (or classifying) the type of vehicle from its acoustic signature. The objective is to broadly classify the vehicle into tracked and wheeled categories, and to further identify the vehicle type within these categories. Most classification algorithms that have been developed for this problem use the relative amplitudes of harmonic components in the acoustic signal as features to distinguish between vehicle types [2]. However, the harmonic amplitudes for a given source may vary significantly due to several factors. For example, the target range, land topography, and meteorological conditions determine the extent of signal degradations caused by frequency-dependent scattering of the acoustic waves as they propagate through the air. The harmonic amplitudes also vary due to engine speed (revving) and the orientation of the source with respect to the sensor (aspect angle).

We can study the limitations on classification accuracy caused by scattering during propagation using models developed in [3]–[7]. Consider the acoustic signal measured at one sensor when a vehicle is in close range. The measured signal is modeled as a sum of L harmonics with fundamental frequency f_0 Hz observed in additive, white, Gaussian noise. The harmonic amplitudes measured at the sensor include the effects of propagation (deterministic power loss and random scattering), source aspect angle, and Doppler. We consider a simple and commonly used processing strategy in which the received average signal power is estimated in L narrow frequency bands centered at the harmonics $f_0, 2f_0, \ldots, Lf_0$. Let us define the following for each band, $l = 1, \ldots, L$:

P_l = average power of the signal at the sensor, including the effects of scattering and noise

S_l = average signal power when there is no noise

$2\sigma_n^2$ = average noise power (same for each band)

Ω_l = "saturation" parameter characterizing the amount of scattering, with $0 \leq \Omega_l \leq 1$ and
- 0 = no scattering (an entirely deterministic signal), and
- 1 = complete scattering (an entirely random signal)

The "signature" of harmonic powers, $S_1, S_2, \ldots, S_L$, is commonly used for source classification. The measurable quantities are the *received* signal powers $P_1, P_2, \ldots, P_L$, so the classification performance depends on the variation of P_l with respect to the unscattered S_l.

It is shown in [3]–[7] that P_l is described by a non-central chi-squared distribution with two degrees of freedom. The pdf of P is plotted in Figure 1(a) for $S = 1$ and $\text{SNR} = -10\log_{10}(2\sigma_n^2) = 30$ dB. Note that small deviations of the saturation Ω from 0 cause significant variations in the received power P around the unscattered signal power $S = 1$, which will limit the performance of classification algorithms. Figure 1(b) shows the variation in saturation Ω with frequency and source range under sunny, calm conditions [6]. These plots show that harmonic amplitude estimates fluctuate by ± several dB for frequencies above 100 Hz and ranges greater than about 40 m.

We are evaluating the potential for improved classification accuracy using additional features, such as aspect angle, range, and velocity information provided by the tracking algorithm. Results based on measured data are presented in [7], which validates fluctuations in harmonic amplitude by several dB, which is consistent with Figure 1(a). The data analysis in [7] also shows considerable variation in vehicle harmonic signatures with speed and aspect angle, suggesting that this information from the tracking algorithm is potentially valuable for the classification algorithm.

References

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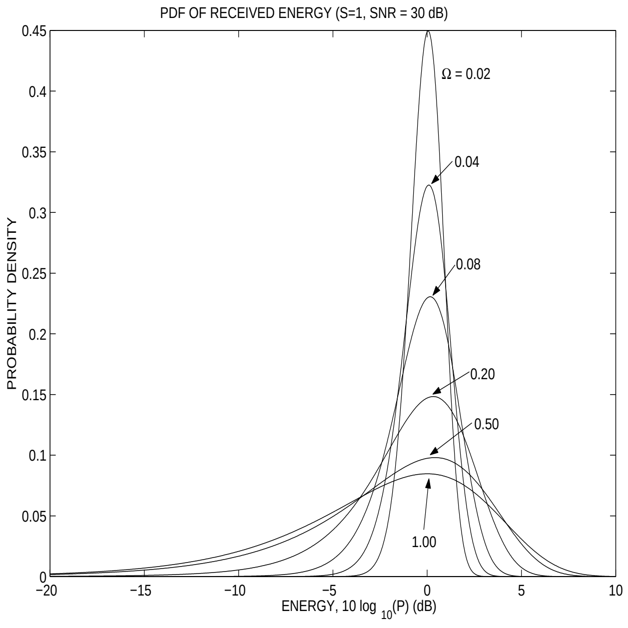
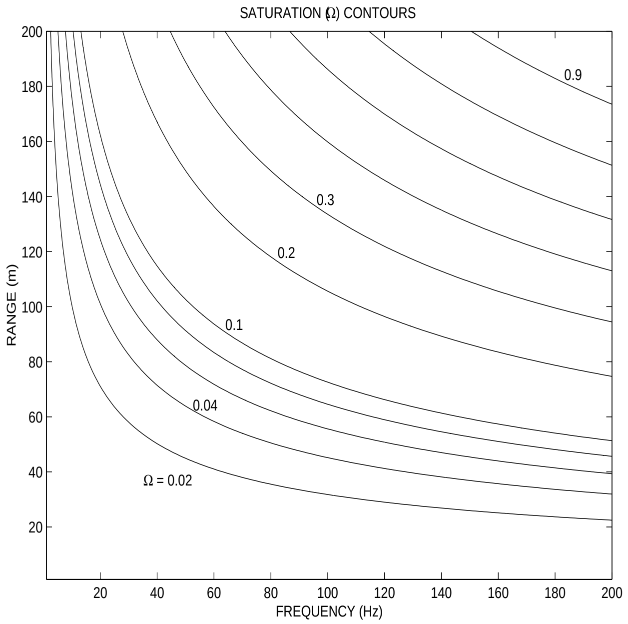


(a)



(b)

Figure 1: (a) Probability density function (pdf) of average power P measured at the sensor for a signal with unscattered average power $S = 1$, SNR $= 1/\sigma_n^2 = 30$ dB, and various values of the saturation Ω. (b) Variation of saturation Ω with frequency f and range r.