Acoustic Target Classification Using Multiscale Methods

K. Eom
The George Washington University
Washington, DC 20052
(202)994-5407, eom@seas.gwu.edu
M. Wellman, N. Srour, D. Hillis
U.S. Army Research Laboratory
Adelphi, MD 20783-1197
R. Chellappa
University of Maryland
College Park, MD 20742

19990106 033

Abstract

This study considers the classification of acoustic signatures using features extracted at multiple scales from hierarchical models and a wavelet transform. In the model-based approach, multiscale spectral features are extracted with hierarchical autoregressive and moving average (ARMA) models. The modeling approach is also used for monitoring vehicular activities from an AR spectrogram. The AR spectrogram shows engine speed, gear changes, and other vehicular activities well, because it represents dominant spectral peaks better than a short-time Fourier transform. In the wavelet-transform based approach, multiscale features are obtained with a wavelet transform. Multiscale classification methods were applied to acoustic data collected at different test tracks under various testing conditions. In this experiment, about 92 percent of vehicles were correctly identified.

Introduction

The classification of ground vehicles using acoustic signals requires reliable features that can classify targets in the presence of background noise and at different signal levels. We propose two types of multiscale features that we have applied to classifying vehicle types in data obtained under various operating conditions. We extracted multiscale features using a hierarchical model and a wavelet transform. In the hierarchical modeling approach, the acoustic signal at the finest scale is modeled by an autoregressive (AR) model. Then the features at coarser scales are obtained by a hierarchical modeling approach from the finer scale features. The multiscale spectral features obtained by the hierarchical modeling approach represent spectral peaks at multiple scales, and many vehicle characteristics, such as engine speed, can be well monitored by the use of spectral features. The wavelet transform expands a signal in a scale space by projecting signals to orthogonal bases, and it compacts the signal low-order wavelet coefficients. Therefore, the set of low-order wavelet coefficients contains sufficient information to classify different targets, and these coefficients can be used as multiscale features.

The classification is done by a minimum distance classifier and an artificial neural network classifier that uses multiscale features. A minimum distance classifier is used with the features extracted by a hierarchical model, and a neural network classifier is applied when the wavelet features are used. Several experiments have been done using ARL acoustic database containing acoustic signals from both tracked and wheeled vehicles. The acoustic signals were recorded at different test tracks under various operating conditions, such as different speed, loading, etc. In the classification experiments, each acoustic signal was segmented into 250-ms-long segments; half the segments were used for training, and the rest for testing. In the classification experiment, up to 92 percent of targets were correctly classified when wavelet features were used.

Hierarchical Model

Suppose that an acoustic signal follows an AR model. Then the acoustic signal is described by AR param-

DTIC QUALITY INSPECTED

AQ I99-04-0517

eters or poles of AR polynomials. The poles of AR polynomials are related to spectral peaks, and dominant spectral peaks are well detected by the power spectral density estimated by an AR model that is fitted to the signal. As we showed elsewhere [4], the models at the coarse scale are determined by the model at a finer scale. Therefore, we can obtain the spectral features at a coarser scale from the AR parameters estimated at a finer scale by using a hierarchical modeling approach. For the acoustic signal experimented with, we first fitted an AR(30) model to the acoustic signal. Using the theorem presented earlier [4], we obtained the model parameters at coarse scales from finer scale parameters without performing expensive smoothing and down-sampling.

For application to acoustic signature classification, we extracted multiscale features at five different scales using the hierarchical modeling approach. At each scale, 15 pairs of complex poles were obtained from an AR(30) polynomial and used as features. From the AR polynomial, the power spectral density can be estimated. By applying the AR power spectrum estimation algorithm at a fixed time interval (for example, every 250 ms), we can obtain an AR power spectrogram. In the experiment, we observed the vehicle activities using the AR power spectrogram.

Wavelet Transform

A wavelet transform, defined by the repeated application of quadrature mirror filters (QMFs), decomposes a signal in a scale space. Figure 1 shows a block diagram of a discrete wavelet transform (DWT) and an inverse discrete wavelet transform (IDWT).

A DWT is an orthogonal transform, and many wavelet bases are available. One of the wavelet bases, known as Coiflet, possesses $2k$ vanishing moments (where k is the order of the wavelet) and has good time-frequency localization characteristics. Figure 2 shows the decimation function and wavelet function of fifth-order Coiflet, and Figure 3 shows the frequency response of fifth-order Coiflets. For the extraction of multiscale wavelet features, we used fifth-order Coiflet basis function.

Experimental Results

The features extracted by hierarchical models and wavelet transforms were used to classify acoustic data collected at Grayling, Michigan, and Aberdeen Proving Ground, Maryland. For the classification of hierarchical model features a minimum distance classifier was used, and a neural network classifier was used for classification of wavelet features.

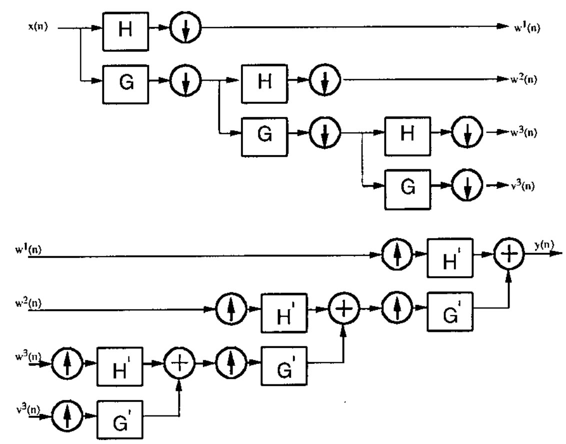

Figure 1: Discrete wavelet transform and inverse discrete wavelet transform.

Acoustic data from ground vehicles were gathered at Grayling and Aberdeen by RNADS [1], a remote sensor architecture. The data set included one tracked and one wheeled vehicle, both powered by a 12 cylinder diesel engines. The remote sensor consists of an 8-ft-diameter circular array of Knowles BL 1994 ceramic microphones, with six microphones placed along the perimeter and a seventh microphone at the center of the array. The vehicle types and test conditions of each test data are summarized in Table 1.

The multiscale feature extraction approaches were applied to the acoustic data. As a test of the accuracy of the classification algorithms, each data file was divided into segments 512 points (250 ms) long. Half the segments were used for training and the rest for testing. Figure 4 shows the AR spectrogram for two data files. Both spectrograms were obtained from a type 2 vehicle, and the data were collected at Grayling. The change in engine speed can be observed from the AR spectrogram. For example, the gear change is detected in the second AR spectrogram in Figure 4.

We extracted the multiscale features using the hierarchical modeling approach. We extracted the spectral peaks at the finest scale by fitting an AR(30) model to the data at the finest scale, and obtanied the features at coarse scales by the hierarchical modeling approach. A minimum distance classifier was trained with half the samples obtained from the data set, and tested with the rest of the samples. In our experi-

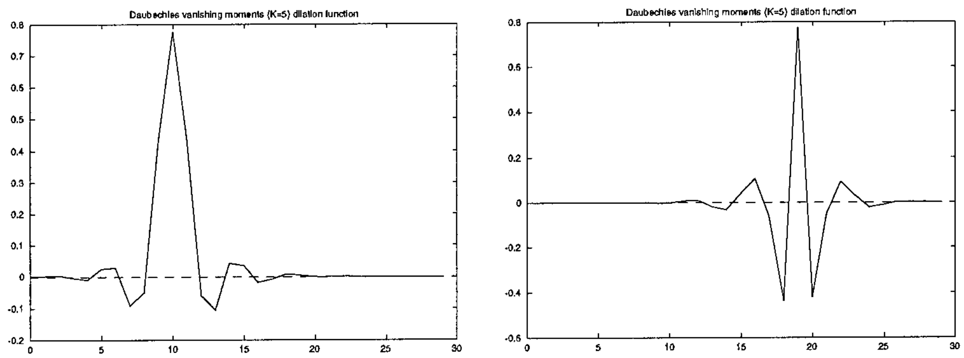

Figure 2: Fifth-order Coiflet decimation function and wavelet function.

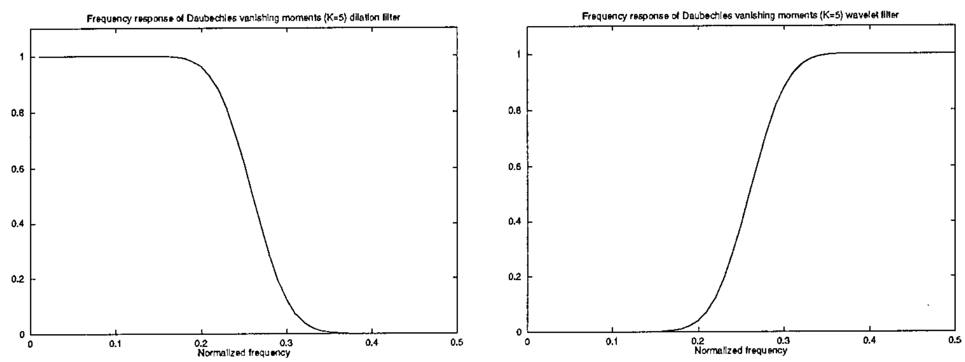

Figure 3: Frequency response of fifth-order Coiflet wavelet: Dilation filter (top) and wavelet filter (bottom).

Table 1: Vehicles tested and test conditions.

Vehicle Type	Test Field	Speed	Other
T1 (tracked)	APG 2	10 mph	sensor 1
T1 (tracked)	APG 2	20 mph	sensor 1
T1 (tracked)	Grayling	10 mph	high gear
T1 (tracked)	Grayling	10 mph	high gear
T1 (tracked)	Grayling	20 mph	high gear
T1 (tracked)	Grayling	20 mph	high gear
T2 (wheeled)	Grayling	15 mph	3rd gear
T2 (wheeled)	Grayling	15 mph	2nd gear
T2 (wheeled)	Grayling	20 mph	3rd gear
T2 (wheeled)	Grayling	20 mph	3rd gear
T2 (wheeled)	Grayling	15 mph	2nd gear
T2 (wheeled)	Grayling	15 mph	2nd gear
T2 (wheeled)	Grayling	20 mph	3rd gear
T2 (wheeled)	Grayling	20 mph	3rd gear

ment, 76.7 percent of the type T1 (tracked) vehicles were correctly classified, and 83.5 percent of the type T2 (wheeled) vehicles were correctly classified.

The wavelet features were also tested. For each data sample, 512 points (250 ms) long, a discrete wavelet transform was applied and wavelet coefficients was computed. In our experiment, a fifth-order Coiflet was used as a wavelet basis function. Figure 5 shows the changes in lower 64 coefficients over time. Each horizontal line represents 64 low-order wavelet coefficients computed from a single segment, 512 points long. The data files used in this experiment are from Grayling, and contain acoustic data from wheeled vehicles in the third gear.

We used neural network classifier to classify acoustic signals using wavelet features. We used 32 low-order wavelet coefficients as features, and applied the back-propagation algorithm for 1000 epochs. Half the data samples of 512 points (250 ms) long were used for training and the rest for testing. The results were that 83 percent of type T1 (tracked) vehicles and 92 percent of type T2 (wheeled) vehicles were correctly classified.

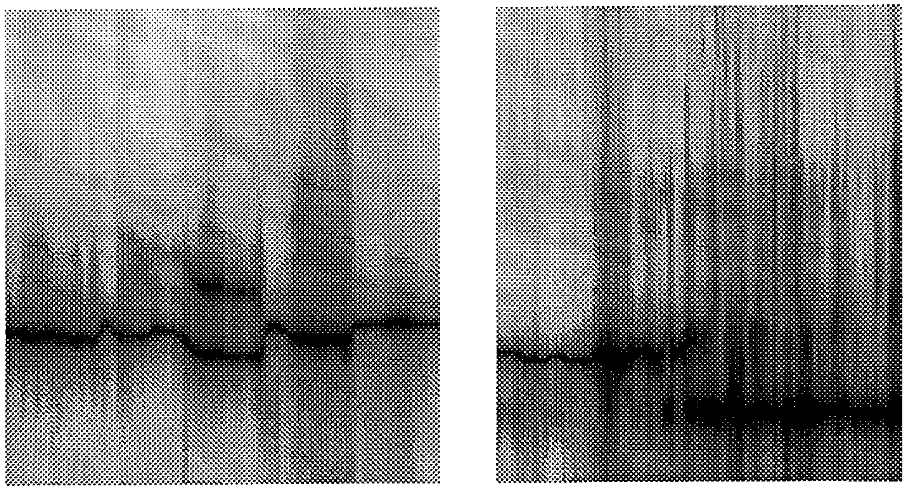

Figure 4: AR spectrogram of two acoustic signatures, gr55s3 and gr58s3. In the second data, the gear change is detected

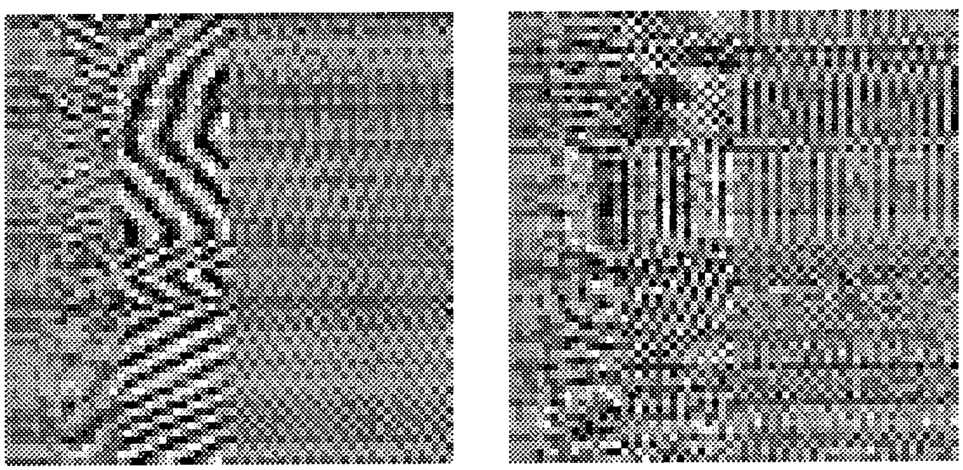

Figure 5: First 64 wavelet coefficients extracted from two acoustic signatures.

Discussions

We have presented classification results with multiscale features obtained by hierarchical modeling and wavelet transforms. In a classification experiment with the ARL acoustic database containing acoustic signatures from tracked and wheeled vehicles at various operating conditions, about 92 percent of targets were correctly classified. More experiment with larger classes and data sets are currently being done, and will be presented in the near future.

References

1. N. Srour and J. Robertson, "Remote netted acoustic detection system," ARL, TR-706, May 1995.
2. K. Eom, "Acoustic data classification using hierarchical models," *Conference Record, 1996 Battlefield Acoustics Symposium*, Ft. Meade, MD, September 24-29, 1996.
3. I. Daubechies, *Ten Lectures on Wavelets,* SIAM Press, 1992.
4. K. Eom and R. Chellappa, "Non-cooperative target classification using hierarchical modeling or high range resolution radar signatures," *Proceeding of SPIE Aerosense '96 Symposium,* Orlando, FL, 1996.
5. S. Mallat, "A theory for multi-resolution signal decomposition: The wavelet representation," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 11, no. 7, pp. 674-693, 1989.

INTERNET DOCUMENT INFORMATION FORM

A . Report Title: Acoustic Target Classification Using Multiscale Methods

B. DATE Report Downloaded From the Internet 1/5/99

C. Report's Point of Contact: (Name, Organization, Address, Office Symbol, & Ph #): U.S. Army Research Laboratory
M. Wellman
Adelphi, MD 20783-1197

D. Currently Applicable Classification Level: Unclassified

E. Distribution Statement A: Approved for Public Release

F. The foregoing information was compiled and provided by:
DTIC-OCA, Initials: VM_ **Preparation Date:** 1/5/99__

The foregoing information should exactly correspond to the Title, Report Number, and the Date on the accompanying report document. If there are mismatches, or other questions, contact the above OCA Representative for resolution.