

Mutiscale PCA analysis in acoustic signals for Vehicle classification in Wireless Sensor Networks

Dr.G.Padmavathi

Professor and Head

Department of Computer Science
Avinashilingam Deemed University
for Women, Coimbatore

ganapathi.padmavathi@gmail.com

D.Shanmugapriya

Lecturer

Department of Information
Technology
Avinashilingam Deemed University
for Women, Coimbatore

ds_priyaa@rediffmail.com

M.Kalaivani

Research Staff

Department of Computer Science
Avinashilingam Deemed University
for Women, Coimbatore

kalaivanim@gmail.com

ABSTRACT

Vehicle acoustic signals have long been considered as important source in identifying its type. In this research acoustic signals generated by each vehicle will be used to detect its presence and classify the type. The goal of mutiscale PCA is to reconstruct a simplified multivariate signal, starting from a multivariate signal and using a simple representation at each resolution level. Mutiscale principal components analysis generalizes the PCA of a multivariate signal represented as a matrix by simultaneously performing a PCA on the matrices of details at different levels. By selecting the numbers of retained principal components, simplified signals can be reconstructed. These simplified signals are used for extracting the features. Classification is done by using the BPN and compared with the PNN and KNN.

Keywords

Wireless Sensor Networks, Acoustic signals, MSPCA, BPN, Vehicle Classification

1. INTRODUCTION

The Wireless Sensor Networks comprise of relatively inexpensive sensor nodes capable of collecting, processing, storing and transferring information from one node to another. These nodes are able to autonomously form a network through which sensor readings can be propagated. Since the sensor nodes have some intelligence, data can be processed as it flows through the network. Sensing devices will be able to monitor a wide variety of ambient conditions: temperature, pressure, humidity, soil makeup, vehicular movement, noise levels, lighting conditions, the presence or absence of certain kinds of objects, mechanical stress levels in attached objects and so on [1].

Copyright © 2010 Advanced Computing Research Society.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Responsibility of the contents of this paper rests upon the authors and not upon ACRS.

These devices will also be equipped with significant processing, memory and wireless communication capabilities. Emerging low-level and low-power wireless communication protocols will enable to network these sensors and it will add a new dimension to the capabilities of sensors. Sensors will be able to coordinate among themselves on a higher-level sensing task. The proposed acoustic sensors can be easily used with infrastructure-less environment such as a large open field. Visual image processing is widely applied in vehicle identification [3]. This approach, however, may not be suitable for sensor networks because a large volume of data needs to be processed. Finally, vehicle identification using sound is the most promising approach. Acoustic sensors can collect acoustic signals to identify the type of moving ground vehicles. Acoustic sensors can be used in sensor networks for applications such as battlefield monitoring and surveillance. They become more and more attractive because of their rapid deployable quality and cheap [4]–[6]. In acoustic sensor processing, classification algorithms play a critical role to identify the type of vehicle, and help to improve the performance of tracking [7].

The popular multivariate statistical method, PCA has been successfully applied in many industry processes that show high-dimensional, noisy and correlated data onto a lower-dimensional subspace. However PCA is static linear transformation in nature, while most of industrial processes have nonlinear characteristics. To overcome the drawbacks of PCA, many nonlinear PCA methods have been developed. Krammer (1991) first proposed a nonlinear PCA based on an auto-associative neural network with a five-layer structure. Dong and MacAvoy (1995) presented an alternative nonlinear PCA approach which uses a principal curve algorithm and neural network. The principal curve algorithm is used to generate nonlinear principal scores and neural network to build a nonlinear PCA model. Schölkopf et al. (1998) proposed a kernel PCA which used kernel functions to complete nonlinear transformation. Lee et al. (2004) used this method for nonlinear process monitoring. Hiden et al. (1999) suggested non-linear principal components analysis using genetic programming. Shao et al. (1999) proposed a nonlinear PCA based upon an input-training neural network. In order to extract dynamic information from multi-scale process data, many approaches based on dynamic analysis and multi-scale analysis have been investigated. Bakshi (1998) proposed multi-scale principal component analysis

(MSPCA) combined with PCA to de-correlate the cross correlation among different variables, in which wavelet analysis was used to capture auto-correlation within individual variable.

Modeling by PCA and its extensions is done at a single scale, that is, the model relates data represented on basis functions with the same time-frequency localization at all locations. For example, PCA of a time series of measurements is a single-scale model since it relates variables only at the scale of the sampling interval. Such a single-scale modeling approach is appropriate if the data contains contributions at just one scale. Unfortunately, data from almost all practical processes are multiscale in nature due to,

- events occurring at different locations and with different localization in time and frequency,
- stochastic processes whose energy or power spectrum changes with time and/or frequency,
- variables measured at different sampling rates or containing missing data.

Consequently, conventional PCA is not ideally suited for modeling of most process data. Techniques have been developed for PCA of some types of multiscale data such as missing data, but the single-scale approach forces data at all scales to be represented at the finest scale, resulting in increased computational requirements.

Classification is one of the important decision making tasks for many real world problems. Classification will be used when an object needs to be classified into a predefined class or group based on attributes of that object. Generally, there are two types of classification problems: binary problem and multiclass problem. While a binary problem is a situation in which an outcome of prediction has to be determined with a decision of Yes or No, where as a multiple classification problem is a condition in which a predicted result is determined as multiple outcomes. The remaining of this paper is organized as follows. Section II describes the vehicle acoustic signals. Section III gives the Multiscale PCA Analysis. Section IV discusses the experimental results. Section V concludes the paper.

2. VEHICLE ACOUSTIC SIGNALS

In this study, the acoustic signals are used as a source for vehicle identification. These acoustic signals are captured by the acoustic sensors mounted in the field as well as on the vehicle. The acoustic sensor in the Smart Dust sensor node is a condenser type microphone. The schematic for a typical condenser acoustic sensor [1][8] is shown in figure 1; it includes a stretched metal diaphragm that forms one plate of a capacitor. A metal disk placed close to the diaphragm acts as a backplate. A stable DC voltage is applied to the plates through a high resistance to keep electrical charges on the plates. When a sound field excites the diaphragm, the capacitances between the two plates vary according to the variation in the sound pressure. The change in the capacitance generates an AC output proportional to the sound pressure, which is an ultra low-frequency pressure variation. A high-frequency voltage (carrier) is applied

across the plates and the acoustic sensor output signal is the modulated carrier. The Figure 2 shows a typical vehicle acoustic signal waveforms.

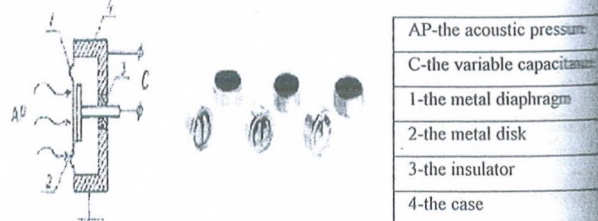


Figure 1: Condenser Microphone

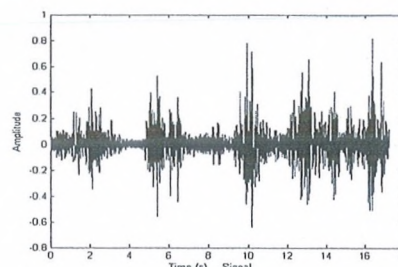


Figure 2: Waveforms of Acoustic Signals Emitted from a Truck

However, the overall acoustic signal of a running vehicle is often much more complicated; the vehicle's sound may come from multiple sources, not exclusively by the engine, but also from tires, brakes, etc. The acoustic signature is made up of a number of individual elements [8]. These include:

- Machinery noise: noise generated by a vehicle engine, propeller shafts, fuel pumps, air conditioning systems, etc.
- Cavitation noise: noise generated by the creation of air bubbles by the turning of a ship's propellers.
- Hydrodynamic noise: noise generated by the movement of water displaced by the hull of a moving vessel.

These emissions depend on a hull's dimensions, the installed machinery and ship's displacement. Therefore different vehicle classes will have different combinations of acoustic signals that together form a unique signature.

3. MULTISCALE PCA ANALYSIS

The aim of multiscale PCA is to reconstruct a simple multivariate signal, starting from a multivariate signal and using a simple representation at each resolution level. Multiscale principal components analysis generalizes the PCA of a multivariate signal represented as a matrix by simultaneously performing a PCA on the matrices of detail of different levels. A PCA is also performed on the coarse approximation coefficients matrix in the wavelet domain as well as on the final reconstructed matrix. By selecting a number of retained principal components, interesting simplified signals can be reconstructed. Figure 3 shows the diagram of MSPCA strategy [9][10][11][12].

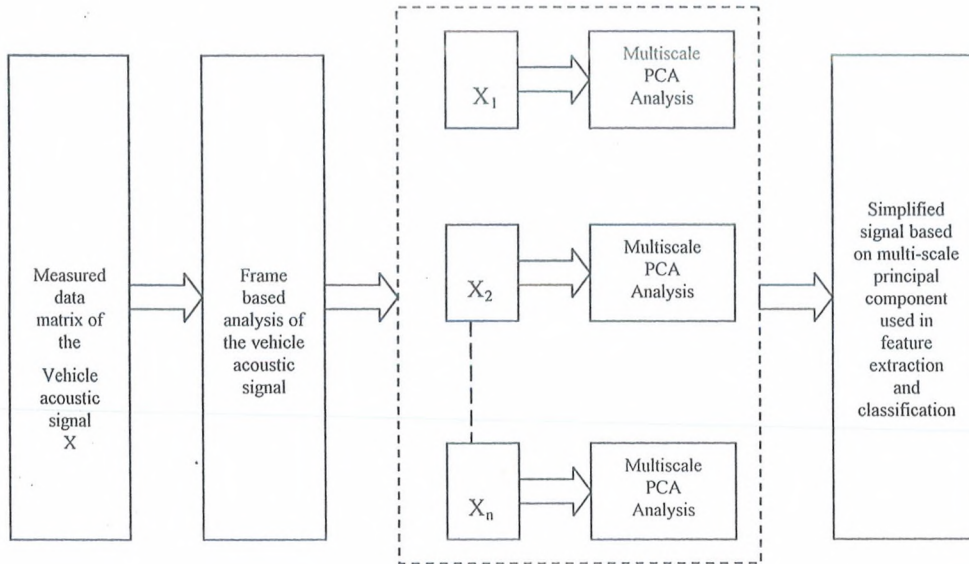


Figure 3: Flow diagram of MSPCA strategy

EXPERIMENT AND RESULTS

The collected samples of all the signals are preprocessed and simplified using MSPCA analysis. The figure 4 shows the simplified signal using MSPCA.

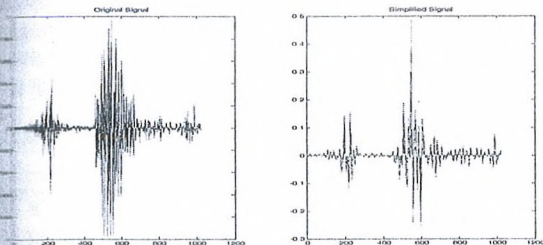


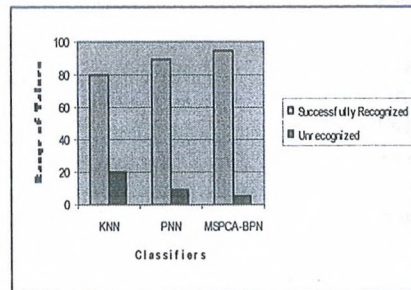
Figure 4: Simplified signal using MSPCA

Features are extracted from MSPCA simplified signal. These signals are further feed into neural network approaches like KNN, PNN and BPN for classification. The following Table gives the result obtained.

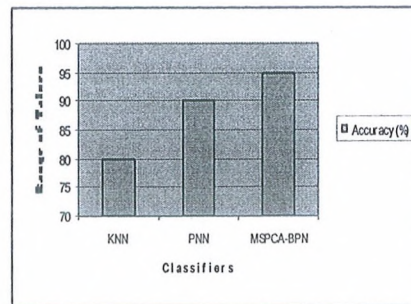
Table: 1 Accuracy obtained

Classifiers	Number of samples	Successfully Recognized	Unrecognized	Accuracy (%)
KNN	100	80	20	80
PNN	100	90	10	90
MSPCA-BPN	100	95	5	95

The accuracy is calculated to evaluate the effectiveness of the neural network approaches in classification. The obtained accuracy of the k-NN is 80%, PNN is 90% and MSPCA-BPN is 95% respectively. The results show that MSPCA-BPN classifier provides more accuracy which is depicted in figure 5.



(a)



(b)

Figure 5: Vehicle classification results (a) successfully recognized and unrecognized rate (b) Accuracy of the classifiers

5. CONCLUSION

In this paper Multi Scale Principal Component Analysis (MSPCA) is used to simplify the vehicle acoustic signals captured through the acoustic sensors. These simplified signals are used for the classification system. Neural network approaches are used to classify the vehicle signals. The classification performance obtained by three different types of neural networks for comparison is k-nearest neighbor (KNN), Probabilistic Neural Network (PNN) and Back Propagation Neural Network (BPN). MSPCA is combined with the BPN for better results and it is proved by calculating the accuracy. The results show that MSPCA with BPN classifier provides more accuracy when compared to others.

6. ACKNOWLEDGMENTS

The authors would like to thank the Armament Research Board (ARMREB-DRDO) for supporting this Research project by funding.

7. REFERENCES

- [1] F. L. Lewis, "Wireless Sensor Networks," Smart Environments: technologies, protocols, and Applications, John Wiley, New York, 2004.
- [2] Lan F. Akyildiz and et al., "A Survey on Sensor Networks," IEEE Communication Magazine, August 2002.
- [3] Seung S. Yang, Yoon G. Kim and Hongsik Choi, "Vehicle Identification using Discrete Spectrums in Wireless Sensor Networks", JOURNAL OF NETWORKS, VOL. 3, NO. 4, APRIL 2008
- [4] H. Wu, M. Siegel, and P. Khosla, Vehicle sound signature recognition by frequency vector principal component analysis. IEEE Transactions on Instrument and Measurement, 48(5):1005-1009, 1999.
- [5] M. Duarte and Y.H. Hu. Vehicle classification in distributed sensor networks. Journal of Parallel and Distributed Computing, 64:826-838, 2004.
- [6] H. Wu and J.M. Mendel. Classification of battlefield ground vehicles using acoustic features and fuzzy logic rule-based classifiers. IEEE Transactions on Fuzzy Systems, 15(1):56-72, 2007.
- [7] T. R. Damarla, T. Pham, and D. Lake. "An algorithm for classifying multiple targets using acoustic signature". In Proceedings of SPIE Signal Processing, Sensor Fusion and Target Recognition, 2004.
- [8] Jiagen Ding, Sing-Yiu Cheung, Chin-Woo Tan and Pravin Varaiya, "Signal Processing of Sensor Node Data for Vehicle Detection," IEEE Proceedings on International Intelligent Transportation Systems Conference, October 2004.
- [9] Tian Xuemin, Deng Xiaogang, "A Fault Detection Method Using Multi-Scale Kernel Principal Component Analysis", Proceedings of the 27th IEEE Chinese Control Conference, Kunming, Yunnan, China, 2008

- [10] Bhavik R. Bakshi, "Multiscale PCA with Application to Multivariate Statistical Process Monitoring", AIChE Journal, 1998
- [11] Zhang Haifeng WANG Yuesheng, "Improved Mspca with Application to Process Monitoring", IEEE conference on International Technology and Innovation, 2006
- [12] Zhiqiang Geng and Qunxiong Zhu, "A Wavelet-Based Adaptive MSPCA for Process Signal Monitoring & Diagnosis", IEEE conference on International Conference on Information Acquisition, 2004

AUTHORS



Dr. Padmavathi Ganapathi is the professor and head of Department of Computer Science, Avinashilingam University for Women, Coimbatore. She has 22 years of teaching experience and one year Industrial experience. Her areas of interest include Network security and Cryptography and real time communication. She has more than 102 publications at national and International level. She is a member of many professional organizations like CSI, ISTE, AACE, WSEAS, ISCA, and UWA.



Shanmugapriya. D, received the B.Sc. and M.Sc. degrees in Computer Science from Avinashilingam University for Women, Coimbatore in 1999 and 2001 respectively. And, she received the M.Phil degree in Computer Science from Manonmaniam Sundaranar University Thirunelveli in 2003 and pursuing her PhD at Avinashilingam University for Women. She is currently working as a Lecturer in Information Technology at the same University and has eight years of teaching experience. Her research interests are Biometrics, Network Security and System Security.



Kalaivani. M, received the BCA from Kovai Kalaimagal College of Arts and Science, Coimbatore and MCA from Avinashilingam University for Women, Coimbatore in 2005 and 2006 respectively. She is currently working as a Research Staff in the Department of Computer Science at the same University. Her research interests are Signal Processing, Sensor Networks.