A NOVEL KNN CLASSIFIER FOR ACOUSTIC VEHICLE CLASSIFICATION BASED ON ALPHA-STABLE STATISTICAL MODELING

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ABSTRACT

This paper describes a novel methodology for statistical modeling and classification of acoustic signals collected from a wireless sensor network. Our SαS kNN classifier is based on a variation of k-nearest neighbor algorithm. First, we perform a 1-D wavelet decomposition of the acoustic signal and we model the resulting subband coefficients using the alpha-stable distribution. Subsequently, the alpha-stable distribution parameters are estimated during feature extraction and the similarity between two acoustic signals is measured by employing a variant of the Kullback-Leibler Divergence (KLD) between the characteristic functions of the corresponding subband representations. We evaluate and compare the performance of the proposed methodology by using actual recorded data in a vehicle classification application.

Index Terms— k nearest neighbor, symmetric alpha-stable distribution, wavelet decomposition, vehicle classification.

1. INTRODUCTION

Pattern recognition aims to classify data based either on a priori knowledge or on statistical information extracted from the measurements. Nowadays, a complete pattern recognition system consists of a sensor network that gathers the observations to be classified, a feature extraction procedure that computes numeric or symbolic information from the observations, and a classification or description scheme that classifies every new observation, relying on a set of extracted features.

A very common non-parametric method is the k-nearest neighbors (kNN) classifier, which is simple but proved effective in many cases. For a data record t to be classified, its k nearest neighbors are computed. Most of the times, majority voting among the data records in the neighborhood is used to decide the classification for t with or without consideration of distance-based weighting. A higher value of k results in a smoother less locally sensitive function. Modern approaches apply the classification scheme not only on the original data representation but also on a transformation of the given dataset, provided an associated distance metric. The reason is that usually specific transformations present a statistical behavior that we can take advantage of.

In this paper, we propose, test and validate with real data a variation of the kNN classifier which we name SαS kNN. Motivated by recent theoretical studies and modeling results by Tzagkarakis et al. in shallow-water acoustic signal classification [1] and texture image retrieval [2], we first employ non-Gaussian data analysis and symmetric alpha-stable distributions (SαS) to represent the wavelet coefficients of signal decomposition subbands and extract informative signal features. Then, we use a variant of the Kullback Leibler divergence for similarity measurement, as a distance function in the kNN classifier. We evaluate and compare the performance of the proposed classifier with common classification algorithms on real data collected by Duarte et al. of the University of Wisconsin Madison within the third SensIT situational experiment (SITEX02) organized by the DARPA/IXOs SensIT program.

2. MULTISENSOR SURVEILLANCE AND VEHICLE CLASSIFICATION

2.1. Vehicle Feature Extraction

Vehicle type classification is an important task in both military and civilian applications including automated traffic monitoring and analysis. The scheme that is considered for this paper is vehicle type classification within a wireless sensor network (WSN). Since sensing devices usually are autonomous and power-limited, a major issue in WSN algorithmic design is energy consumption. As the radio is the main cause of power consumption in a sensor node, transmission/reception of data should be limited as much as possible. On the other hand, depending on the frequency and duration of a recording, each sensor collects hundreds or even thousands of recorded

This work was funded by the Marie Curie TOK-DEV "ASPIRE" grant (MTKD-CT-2005-029791) within the 6$^{\text{th}}$ European Community Framework Program.

values. Transmitting all these values in order to classify an object requires more energy than a battery can handle. Minimization of energy consumption can be achieved by modeling and representing data efficiently.

Recently, related research has focused on local classification [3] combined with global decision fusion [4] and distributed techniques for training and classifying new samples [5]. In this paper, we concentrate on the efficient measurement representation and feature extraction and we consider a centralized training and classification framework. Distributed implementations of the SαS kNN classifier will be addressed in the future. In the original experiment described in [6], each run consists of a single vehicle following a specific road with a constant speed. In the experiment, two different vehicle classes were used, namely Assault Amphibian Vehicle (AAV) and Dragon Wagon (DW). The objective was to detect and identify vehicles when they pass through a region. Once there was a positive detection, a pattern classification algorithm is run to classify the vehicle according to its acoustic/seismic signature. The "signature" *feature vectors* used! for classification are collected from the raw data by taking an FFT transformation for every 512 point sample and by chosing the first 100 points. The points were averaged by pairs, resulting in a 50-dimensional FFT-based feature vector.

In our approach, the statistical modeling and the associated feature extraction module of the classifier are based on the observation that acoustic signals present a burst behavior and tend to be sparse in the wavelet domain. In particular, in our experiments we used a 3 level decomposition employing Daubechies 4 wavelet [7]. At the first phase using a one dimensional orthogonal discrete wavelet transform(DWT) the original signal is decomposed into low-frequency *approximation components* and high-frequency *detail components*. By repeating the decomposition process on the previous level approximation components, the original signal is transformed into a set of detail subbands, each corresponding to an average timescale that doubles at each level, and an approximation subband. Generally, a N-level decomposition of a signal results in $N+1$ subband coefficients, N detail and 1 approximation.

2.2. Alpha-Stable Modeling of Vehicle Features

It has been pointed out that the wavelet transformation of bursty signals tends to be sparse. This property gives rise to heavy-tailed and peaky *non-Gaussian* marginal distributions of the wavelet subband coefficients. The *symmetric alpha-stable* (SαS) distributions have been proven to be efficient in describing signals with an impulsive nature. In contrast to the Gaussian density whose tails are exponentially bounded, stable densities have an algebraic rate of decay.

Due to lack of closed formulas for most stable densities and distribution functions,the SαS distribution is best defined by its characteristic function:

$$\phi(\omega) = exp(i\delta\omega - \gamma|\omega|^{\alpha}),$$

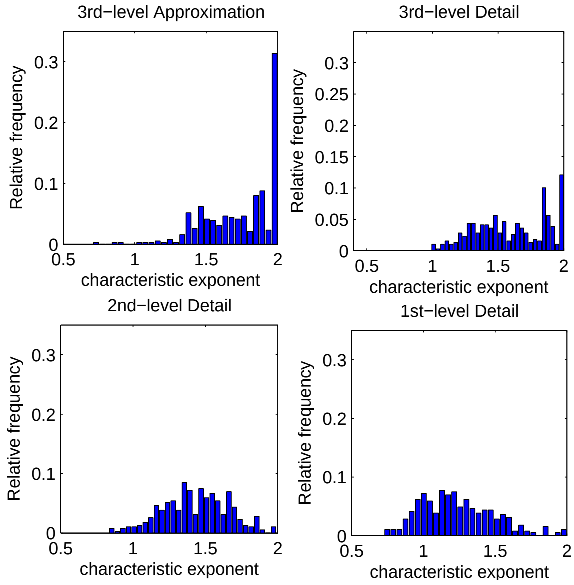

Fig. 1. Histograms representing the relative frequencies of the estimated characteristic exponent α for the acoustic signal decompositions of the SensIT acoustic dataset. Deviations of α from the value 2 indicate that the data is non-Gaussian.

where α is the *characteristic exponent* taking values $0 < \alpha \leq 2$, $\delta(-\infty < \delta < \infty)$ is the *location parameter*, and $\gamma(\gamma > 0)$ is the *dispersion* of the distribution. The location parameter δ corresponds to the mean of the SαS distribution for values of α in the interval (1,2], while for $0 < \alpha \leq 1$, δ corresponds to the median. Similar to the variance of the Gaussian distribution, the dispersion parameter γ determines the spread of the distribution around its location parameter δ. The shape of the distribution is determined by its characteristic exponent α. The smaller the value of α, the heavier the tails of the density. For values $\alpha = 1$ and $\alpha = 2$, we get the Cauchy and Gaussian densities, respectively.

The feature vector of a recording is formed by estimating the (α, γ) pairs at each wavelet decomposition subband. Thus an acoustic signal S, decomposed in $N = 3$ levels has 4 subbands and each subband is modeled with a SαS distribution. So, a set of 4 pairs of estimated parameters will constitute our feature vector. In general:

$$S \rightarrow \{(\alpha_1, \gamma_1), (\alpha_2, \gamma_2), ..., , (\alpha_N, \gamma_N), (\alpha_{N+1}, \gamma_{N+1})\},$$

where (α_N, γ_N) are the estimated model parameters of the N-th subband. Figure 1 displays the histograms of the estimated characteristic exponent values for the acoustic recordings of the SensIT situational experiment data. By our statistical approach we have modeled thousands of coefficients at each subband, into a single pair of parameter. So for a N-level decomposition, $2(N+1)$ parameters are enough to describe a specific bursty acoustic signal. Figure 1 clearly demonstrates that the coefficients of different subbands and decomposition levels exhibit various degrees of non-Gaussianity, which could

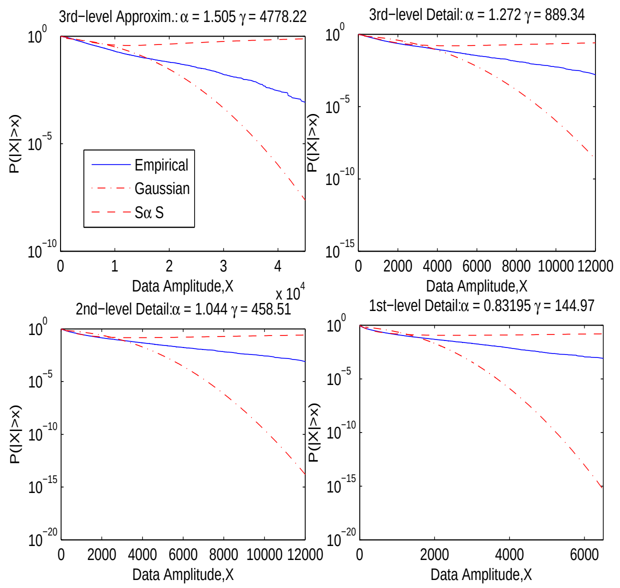

Fig. 2. Four wavelet subbands of a three-level decomposition of dw7event5_1_1.txt signal are modeled with SαS and GGD APDs depicted in dashed and dash-dotted lines, respectively. The solid line denotes the empirical APD. The SαS distribution is superior to the GGD because it provides a better fit to both the mode and the tails of the empirical density of the actual data.

be very informative when constructing a classifier.

As a further stability test, Figure 2 employs amplitude probability density (APD) curves $(P(|X|) > x)$ to examine whether the SαS fit matches the data near the mode and on tails of the distribution. Along with the SαS , a generalized Gaussian density (GGD) fit is also compared with the empirical curve at each subband of a randomly chosen decomposed acoustic signal. The empirical APD $P(|X|) > x$ is computed as the percentage of the wavelet coefficients with amplitude greater than x, with x varying between 0 and a maximum value determined as the maximum amplitude of the available set of wavelet coefficients. Clearly, the SαS density is superior to the GGD, following more closely both the mode and the tail of the empirical APD, than the exponentially decaying GGD.

3. SAS-KNN CLASSIFER

In order to apply a kNN classification scheme, a distance measurement should be chosen. In [8], Do and Vetterli used the Kullback -Leibler Divergence as the similarity measurement for GGDs. In the SαS case, there is no closed-form KLD expression between two general SαS distributions. Instead, KLD can be applied between normalized versions of the corresponding characteristic functions as shown in [9]:

$$D(\hat{\phi_1}||\hat{\phi_2}) = ln\Big(\frac{c_2}{c_1}\Big) - \frac{1}{\alpha_1} + \Big(\frac{\gamma_2}{\gamma_1}\Big)^{\alpha_2} \cdot \frac{\Gamma(\frac{a_2+1}{\alpha_1})}{\Gamma(\frac{1}{a_1})},$$

where (α_i, γ_i) are the estimated parameters of the characteristic function $\phi_i()$, and c_i is an associated normalizing factor given by

$$c = \frac{2\Gamma(\frac{1}{\alpha})}{\alpha\gamma}.$$

It is shown [9] that $D(\hat{\phi_1}||\hat{\phi_2}) \geq 0$ with equality if and only if $(\alpha_1, \gamma_1) = (\alpha_2, \gamma_2)$.

In our work, we have modeled every subband with a different SαS distribution. Additionally, assuming that the wavelet coefficients of different subbands are independent, the overall distance between two acoustic signals S_1, S_2 is measured as

$$D(S_1||S_2) = \sum_{k=1}^{N+1} D(\phi_{S_1,k}||\phi_{S_2,k})$$

Finally, taking into consideration that a symmetry property must hold for a distance function we define a symmetrized version of the KLD as follows:

$$D_{sym}(S_1||S_2) = \frac{D(S_1||S_2) + D(S_2||S_1)}{2}$$

This symmetrized version satisfies all the properties that a distance function should have.

Given a training dataset with acoustic signals modeled as described in Section 2 SαS kNN classifies any new sample, first by modeling and then by computing the majority class membership of the k closest training data points. A choice of small k value, will cost less computing resources and less energy, a factor that we always consider at WSN.

4. EXPERIMENTAL RESULTS

In this Section, experiment specifications and classification results are analyzed. We tested and compared 4 different classifiers, namely, the SVM with a RBF kernel, the kNN with k chosen by parameter selection, the Gaussian-kNN model where α=2 and the variance is computed over the wavelet coefficients of each subband, and finally the proposed SαS kNN classifier. Both GG kNN and SαS kNN consider the class of their 10 closest neighbors ($K = 10$). To maximize the accuracy of our results a 10-fold cross validation (CV) was performed.

In Table 1 detection, false alarm and classification rates are presented. As for performance metric, the area under the receiver operating characteristic curve (AUC) was computed for every train-test process of 10-fold-CV. The average of AUC values as well as the variance, are presented at the last two columns of Table 1. The AUC metric is the most suitable choice due to two-class nature of our dataset. As we observe from Table 1, the SαS kNN model has the best detection rate for the AAV vehicle class and a competitive rate for the DW vehicle class. The proposed SαS -kNN model yields out the best average-AUC and the best classification rate. The

Measurement	Detection Rate		False Alarm Rate		Classification	Average	Variance of
Class	AAV	DW	AAV	DW	Rate	AUC	Average AUC
SVM	69,9%	**96,9%**	30,1%	3,1%	82,2%	0,852	32×10^{-4}
KNN	88,9%	80,7%	30%	40%	85,2%	0,867	7×10^{-4}
GG-KNN	92,8%	83,9%	7,2%	16,1%	88,7%	0,906	17×10^{-4}
SαS -KNN	**94,3%**	88,9%	5,7%	11,1%	**91,8%**	**0,937**	31×10^{-4}

Table 1. Detection, False Alarm and Classification Rates using 10-way cross validation for different classifiers on acoustic modality for SensIT real data. High values of average-AUC, classification and detection rates imply better classification performance.

Total		
SVM	305	131
	11	353
KNN	388	48
	70	294
GG-KNN	194	15
	29	151
SαS -KNN	197	12
	20	160

Table 2. Confusion matrix for each classifier using 10-fold cross validation. Even though the number of samples for the GG kNN and SαS kNN classifiers differs from the SVM and kNN, the proposed SαS kNN achieves better classification results.

variance of average-AUC though, is not the lowest compared with the other models.

In the original experiment [6], each signal produced a non-constant number of 50-dimensional FFT feature vectors. From this data set, we randomly chose 800 samples from both classes. On the other hand, for SαS modeling each signal was considered as one sample for classification. This fact justifies the difference in the number of samples that we observe at Table 2. Despite this difference, the SαS kNN model obtain a better performance.

In conclusion, although this real life problem is quite simple (two-class, centralized processing), the statistical modeling that we propose achieves better classification results with less data for transmission/reception. Such an approach can offer a great amount of energy savings and speed improvements in a Wireless Sensor Network.

Acknowledgments

We would like to thank the SensIT / Collaborative Signal Processing Research Group, ECE Department, University of Wisconsin Madison for sharing data and results collected at the third SensIT situational experiment (SITEX02), organized by DARPA/IXOs SensITprogram [6].

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