Paper

A simple vehicle classification framework for wireless audio-sensor networks

Baljeet Malhotra, Ioanis Nikolaidis, and Janelle Harms

Abstract—Vehicle tracking is one of the important applications of wireless sensor networks. We consider an aspect of tracking: the classification of targets based on the acoustic signals produced by vehicles. In this paper, we present a naïve classifier and simple distributed schemes for vehicle classification based on the features extracted from the acoustic signals. We demonstrate a novel way of using Aura matrices to create a new feature derived from the power spectral density (PSD) of a signal, which performs at par with other existing features. To benefit from the distributed environment of the sensor networks we also propose efficient dynamic acoustic features that are low on dimension, yet effective for classification. An experimental study has been conducted using real acoustic signals of different vehicles in an urban setting. Our proposed schemes using a naïve classifier achieved highly accurate results in classifying different vehicles into two classes. Communication and computational costs were also computed to capture their trade-off with the classification quality.

Keywords*— *sensor networks, vehicle classification, acoustic signals.

1. Introduction

Networked sensors can be equipped with various sensing devices, as well as memory, processor, radio, and a power supply. However, they are still constrained by limited memory, processing power, channel capacity, and, most importantly, energy reserves. When tracking is considered as an application, data-intensive sources (e.g., high frame rate/high resolution video) is usually avoided as being more energy expensive than low data rate sources. For this reason tracking using audio signals is usually preferable. Vehicle tracking on acoustic data is based on the fact that different vehicles produce distinctly different acoustic signals because their engine and propulsion mechanisms are unique [12]. The problem of vehicle detection using the acoustic signature has been extensively studied [2, 12, 14]. Recently, target classification based on acoustic signals in wireless sensor networks has been addressed in [4, 9]. The advantage of sensor networks is that they provide redundancy in terms of sensing and processing units. Hence, they can operate together in a distributed and coordinated fashion to detect and report the presence of a target vehicle, possibly refining the tracking and classification quality as the target is moving.

We should add that vehicle tracking includes various objectives that must be supported by a number of steps. These steps include vehicle detection, identification and/or classification, and localization. Depending on the specific tracking objectives, all or combinations of these steps may be required. In this paper we restrict our attention to classification alone. Classification is necessary because sensors can report on a specific moving vehicle only after they recognize vehicles that are of some interest. Classification is naturally more challenging if there are multiple targets of various types (e.g., tanks, jeeps, other types of military vehicles, civilian vehicles, etc.). Furthermore, there may be a number of vehicles of the same type, e.g., tanks of a particular make. We define as *classification* the problem of identifying which class a vehicle belongs to. Identifying a *particular* vehicle goes one step further and is not within the scope of the current paper.

Various techniques have been proposed to address the classification problem [2, 4, 12], relying on *feature extraction* that differ in the way features are extracted. For example [2], proposed a wavelet based method for feature extraction, which works as follows: three different types of acoustic signature are extracted: squeak sound, sound under motion, exhaust sound.

The data points contained by each of these signatures are decomposed to a 12 element feature vector using the multiresolution analysis [10]. These 12 element feature vectors represent the energy concentration of the signature signal at 12 different resolution levels. The continuous wavelet transform (CWT) and the Short-Term Fourier transform (STFT) plots were used for two other feature vectors. Finally, these feature vectors are used to compute the distance between the reference and unknown signatures. Wu *et al.* in [14] proposed a principle component analysis based method for recognition of acoustic signatures. The basic idea of their proposed method is to use together the mean adjusted sound spectrum, and key eigenvalues of the covariance matrix to characterize an acoustic signature.

An adaptive threshold based algorithm is proposed in [3] for vehicle detection, based on the average energy of an acoustic signal crossing a threshold value before a decision on the detection of the vehicle can be made. The threshold is updated adaptively. Also, [4] details experiments carried out during the 3rd SensIT situational experiment (SITEX02) organized by DARPA/IXO. Various military vehicles were used in these experiments, real word data was generated and archived for future studies. The objective was to detect and accurately locate vehicles using energy-based localization algorithm. Frequency spectrum based features are extracted from the acoustic and seismic signals captured by the sensors. These features were extracted by using 512-point fast Fourier transform (FFT). Then, for classification purposes, three different approaches are used, i.e.:

- k-nearest-neighbor classifier,
- maximum likelihood classifier,
- support-vector-machine classifier.

In [9] a framework for collaborative signal processing in sensor networks is designed for the purpose of multiple targets detection, classification, and tracking.

In this paper we study the impact of increasing the complexity and memory footprint of a classification algorithm to achieve better classification accuracy. We consider this to be a reasonable trade-off since what is usually assumed to be expensive in terms of energy is communication, and not computation/storage (within reason of course). While we are also increasing the computation cost, we argue that as long as the computation is allowed to be completed within a reasonable amount of time, computation can be spread over a longer period of time by proper reduction of the CPU clock [16].

One distinct contributions of our work is that in order to maximally benefit from the information collected by a sensor, we consider multiple representations of features. Some, are well known (FFT, PSD, etc.) but we also introduce *Aura matrices*. Aura matrices [6] have been used in the past for analyzing and predicting texture patterns [15]. In our study we create "artificial" 2-dimensional "textures" by arranging PSD data into matrices, and then using Aura matrices to summarize the information of the 2-dimensional matrix. In other words, Aura matrices attempt to visually approximate the arrangement of PSD values. For details about the construction of Aura matrices the reader is referred to [6]. To exploit the inherently distributed environment of the sensor networks we also propose dynamic PSD features, which are generated on the *run* by the sensors as they capture the acoustic signals. The distinct contribution of the dynamic PSD features is that they are quite low on dimension, yet, effective to produce good classification results.

We start by describing a naïve classification scheme and elementary forms for a distributed implementation over a sensor network in Section 2. Section 3 presents the details on the acoustic features used in this study. Section 4 presents performance evaluation results in terms of classification accuracy and energy expenditure trade-offs for the different distributed implementations. Finally, Section 5 summarizes the findings of the paper and outlines future research objectives.

2. A naïve classifier

Existing techniques such as k-nearest neighbor (k-NN) can be used by sensors to perform the classification. k-NN is based on the idea that similar objects are closer to each other in a multidimensional feature space. k-NN is one of the simplest, yet accurate, classification methods and recently it has been used in sensor networks for target classification [4, 9]. Unfortunately, finding k for the optimum solution is non-trivial. In contrast to k-NN algorithm we adopt a naïve approach where first a training set $|U|$ is defined for each class of the vehicles. Equal number of samples are assumed to be in the training set of these classes. Note that class labels of the training samples are known in advance. Now in order to classify an unknown sample using a particular feature, the naïve classifier does the following: for each class, and for each sample of the $|U|$ samples in the training set of each class, it calculates the distance of the unknown sample from the training set samples. Classifier determines the average distance of the unknown sample from the training set samples of each class. The unknown sample is determined to be in the class with the smallest average distance. If we assume $m \times n$ to be the size of the feature vectors extracted from each of the samples from the set $|U|$ of a class. Furthermore, if we assume there are total c training classes, then the number of computations performed by the classifier to compute the similarity measure for all training classes is proportional to $|U| \times c \times m \times n$. It is clear from this discussion that the dimensionality of the feature vectors is important to the naïve classifier in terms of computational cost. Feature selection is also important for a classifier to achieve good classification results [5]. We discuss more on features selection in Section 3.

Classification process. As a vehicle crosses through an area monitored by a sensor network, the nodes self-organize in neighborhood "clusters" using a technique similar to [1] but where the tie breaking criteria for selection of the "master" node is the signal quality of the monitored vehicle. The master is the node with higher average power of received signal, hence possibly closest to the vehicle. Multiple neighborhoods may be formed, but with a single master node per neighborhood. After the selection, a master node prepares a *schedule*, and broadcasts it in its neighborhood to initiate the classification process. A *schedule* basically consists of *classification assignments* for all sensors in the neighborhood. A typical *classification assignment* for a sensor is to compute the similarity measure of an unknown sample w.r.t. the training samples as specified in the *schedule*. Sensors in a neighborhood after completing their assignments reply back to their master node with their results. After collecting the results the master node makes a decision on the class of the unknown vehicle. Each of the individual neighborhoods can perform a classification method independently of the other neighborhoods. However, multiple neighborhoods may collaborate with each other for two main reasons:

- better accuracy in classifying a vehicle,
- sharing the costs associated with classification.

In our study we examined various scenarios of single and multiple neighborhoods based classification. We propose four basic schemes:

- **Single neighborhood using local signatures (SN-LS).** In this scheme each sensor in a neighborhood predicts the class of the unknown vehicle using a vehicle's local signature captured by the sensor itself. The master node collects results from all sensors in the neighborhood and classifies the unknown vehicle based on the majority of predictions.

- **Single neighborhood using global signatures (SN-GS).** In this scheme each sensor in a neighborhood predicts the class of the unknown vehicle using a vehicle's global signature. A global copy of vehicle's signature is transmitted to a sensor by the master node of its neighborhood. A sensor after receiving global signature from the master node fuses it with its own local signature by using an appropriate averaging function. Master node collects results from all participating nodes in the neighborhood and classifies the unknown vehicle based on the majority of predictions.

- **Multiple neighborhood using local signatures (MN-LS).** In this scheme a master node not only collects results from sensors in its own neighborhood, but it also invokes its adjoining neighborhoods to seek the classification results. All sensors in participating neighborhoods use their local copy of a vehicle's signature.

- **Multiple neighborhood using global signatures (MN-GS).** The basic difference between this scheme and the previous scheme (MN-LS) is that sensors in a particular neighborhood use a global copy of a vehicle's signature provided to them by their respective master node.

3. Features extraction

Sensors perform classification using the features extracted from the acoustic signatures they capture locally or provided to them by their master node. A vehicle's sound is a stochastic signal. The sound of a moving vehicle observed over a period of time will not be a stationary signal. However, a signal of fairly short duration can be treated as a stationary signal [14]. In our case we chose the signal's duration to be 11.06 ms, i.e., 256 data points sampled at a frequency of 22 kHz. In our study we considered six acoustic features that are generated using FFT and PSD of the time series data of a given signal.

1. **Linear FFT feature (LFFT).** This feature is generated using FFT of 256 data points that gave us a linear vector (of size 256) representing frequencies with a resolution of 85.93 Hz.

2. **Linear PSD feature (LPSD).** This feature is generated by taking power spectral density estimates of 256 data points. With a resolution of 85.93 Hz this method gave us a linear vector (of size 128) to form a linear PSD feature.

3. **Multidimensional FFT feature (MFFT).** In this case 10 blocks of 256 FFT data points are used to form a multidimensional FFT feature. This feature can be seen as a matrix of size 256×10. The size 10 was determined by trial and error method.

4. **Multidimensional PSD feature (MPSD).** In this case 10 blocks of 128 PSD data points are used to form a multidimensional PSD feature. This feature can be seen as a matrix of size 128×10.

5. **Aura of a multidimensional PSD feature (AMPSD)**. It has been demonstrated in [7] that PSD is not an optimal feature for signal recognition. We sought to improve the PSD based feature using some established statistical techniques, namely Aura matrices. In order to construct AMPSD features we simply compute Aura of a MPSD matrix. For computing the Aura of a matrix the reader is referred to [6].

6. **Dynamic multidimensional PSD feature (DMPSD)**. One limitation of the multidimensional features is their size. Consider the MPSD feature which is a 128×10 matrix. In order to classify an unknown sample, the naïve classifier must compute the similarity measure of the unknown sample w.r.t. all training samples in all the classes. That may make the naïve classifier computationally expensive for any real time application. Sensors can adopt a dynamic approach here. After constituting a MPSD feature, each sensor may choose only selective PSD dimensions. One criterion for selection is to choose only those dimensions that have the maximum value in each of the blocks (of 128 PSD points). For example, if there were only two blocks of PSD data, and if the first PSD block had a maximum value in the d_1 dimension, and the second PSD block had the maximum value in the d_5 dimension, then only d_1 and d_5 dimensions are selected for both the blocks (of 128 PSD points) to create DMPSD (dynamic MPSD) feature. In this particular example, the DMPSD feature is a matrix of size 2×2.

The FFT and PSD data of each of the training samples from all the training classes can be extracted *off-line* and uploaded to the sensors in advance before their deployment. After deployment sensors must extract FFT/PSD features from the unknown samples *on-line*. In the case of LFFT, LPSD, MFFT, MPSD, and AMPSD features, the dimensions of the training FFT/PSD data are fixed. However, in the case of DMPSD feature, sensors must adjust the dimensions of the training PSD data according to the dimensions of the DMPSD feature of the unknown sample that is being classified. In our experimental study, which is presented next, we evaluate the performance of the above discussed features in terms of their accuracy, communication, and computational costs.

4. Experimental study

We used acoustic signal samples of various urban ground vehicles, recorded using a Panasonic US395 microphone. Approximately 50 samples of various vehicles were recorded at two main locations of Bonnie-Doon mall and the University of Alberta bus stop in the city of Edmonton. The samples included ETS buses (part of the public transportation system at the city of Edmonton), different types of cars, small trucks, SUVs, and mini vans. All samples were transferred to MATLAB for the simulation of classification algorithms. We standardized our acoustic dataset to remove any shifting and scaling factors by using the *normal form* [8] of the original time series data.

We assume that every sensor has a copy of training set, U for each class. A sensor's captured signal of an unknown vehicle, which needs to be classified, may be different from other sensors signal of the same unknown vehicle captured approximately at the same time because of the different sensors positions. In order to create a local copy of an unknown signature for a sensor, we attenuate the original signal based on the distance of the sensor from the moving vehicle. Then, we introduce time difference of arrival (TDOA) lags for multiple sensors capturing the same signal based on their relative position, and also add white noise. A vehicle's sound can also be degraded by reverberations, however, we considered an outdoor open environment, so we have neglected the effect of reverberations. In our simulation we considered various scenarios for sensor setup. In these experiments sensors are assumed to be placed along two straight parallel lines, i.e., as they would be deployed along the sides of a street. Sensors are placed 5 m apart and their sensing and radio range is 15 m. A vehicle is considered to be moving with a speed of 53±2 km/h.

4.1. Performance metrics

We consider three performance metrics:

- classification accuracy,
- communication overheads,
- computation cost.

Classification accuracy is computed based on the leave-one-out policy. Under this policy one sample is removed from the acoustic dataset consisting of all samples in a class. This sample is called the testing sample. The rest of the samples in the dataset constitute the training set U for that class. Class label of the testing sample is assumed to be unknown. Then, the distance of the testing sample is computed from all the samples in the training set of each class. This process is repeated for all samples in our acoustic dataset. If two samples are represented by matrices $X_{m\times n}$ and $X'_{m\times n}$, then the distance between them is computed as follows:

$$d = \sum_{q=1}^{|n|} \sum_{p=1}^{|m|} |x_{pq} - x'_{pq}| \,. \tag{1}$$

Classification accuracy is calculated as a percentage of testing samples that are correctly classified from the total number of testing samples. In the experiments we used a simplistic case of only two classes. The objective was to classify the previously mentioned vehicles into two classes, i.e., ETS buses and other vehicles that are not ETS buses. Communication overheads are computed based on the number of bits transmitted by a sensors per classification event. Computational costs are based on the number of computations performed by a sensor per classification event to measure the similarity difference between the unknown sample and the training samples in all classes.

4.2. Single neighborhood case

The results for classification accuracy in SN-LS and SN-GS schemes are presented in Fig. 1. In these experiments we vary the number of sensors in a single neighborhood such that all sensors in the cluster are able to communicate to the master node. In that way we vary the cluster size from 3 sensors to 90 sensors in the cluster. The classification accuracy using most of the features, except DMPSD feature, remains the same as the cluster size changes from 3 to 90 sensors. The classification accuracy of DMPSD feature improved from 77% to 90% as the cluster size changed. The reason for improved accuracy is that sensors dynamically select the PSD points as they capture the unknown signal. When the large number of sensors are available in the cluster, the probability of sensors selecting the effective features increases. As the sensors in a neighborhood make their individual decision, an increase in the number of sensors selecting the effective features increases the probability of that particular neighborhood making a correct prediction.

The reason for the lack of improvement using the rest of the feature extraction schemes is that sensors use only a fixed set of features on the training dataset. Adding more sensors into the neighborhood improves the approximation of the distance measurements collected from the multiple sensors from a neighborhood. However, in the case of naïve classifier, these improved approximations did not improve the classification accuracy much. An accuracy of 98% is achived using MPSD and AMPSD features that is better than the accuracies reported in [11], which uses k-NN classifier. As shown in Fig. 1, DMPSD feature's performance improved clearly in both the SN-LS and SN-GS schemes. With a better copy of vehicle's signal available to all participating sensors, features in SN-GS scheme performed slightly better than SN-LS.

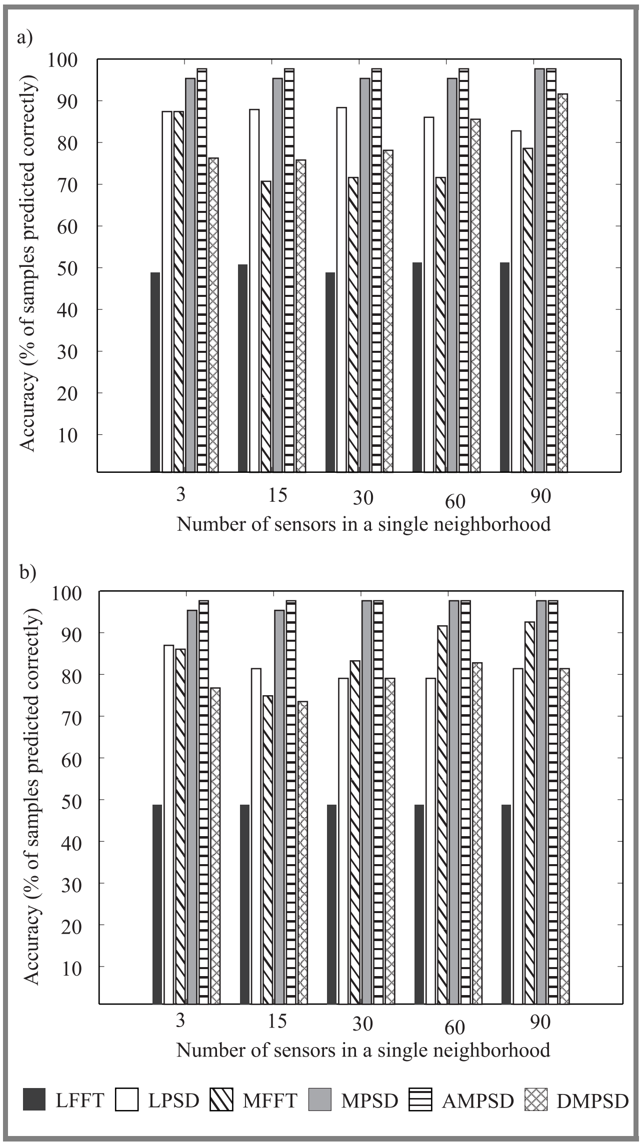

Fig. 1. Classification accuracy of the single neighborhood case: (a) SN-LS; (b) SN-GS.

Increasing the number of sensors in a neighborhood has more impact on the communication costs than on the classification accuracy. The results for SN-LS and SN-GS schemes are presented in Fig. 2a and 2b, respectively. As the number of sensors increases the number of messages exchanged increases. Therefore, costs increase for both the single neighborhood based schemes. Communication costs are much higher in the SN-GS scheme due the transmission of the signature by the master node to its neighborhood.

The benefits of smaller feature size in terms of computational cost are summarized in Fig. 2c. The average size of the DMPSD feature is 6×10, which is almost 4, 2, 42, 21, and 21 times less than LFFT, LPSD, MFFT, MPSD, and AMPSD features, respectively. Due to the reduced feature vectors size, the cost for computing similarity measure in naïve classifier using DMPSD feature is the least as compared to the other feature vectors. On the other hand

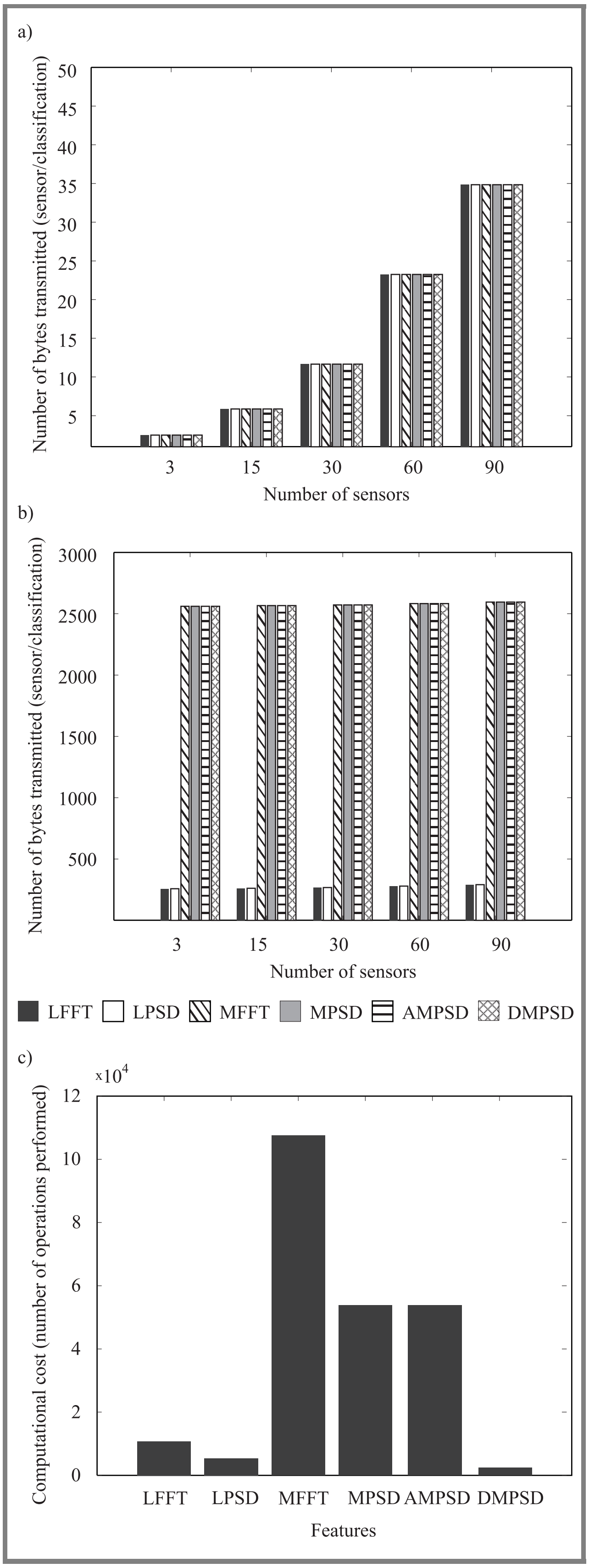

Fig. 2. Cost for the single neighborhood case: (a) communication cost for various features in SN-LS; (b) communication cost for various features in SN-GS; (c) computation cost of similarity measure for various features using the naïve classifier.

MFFT and MPSD are the most expensive features to use. The cost of computing Aura of MPSD is not included in the results of AMPSD feature shown in Fig. 2c.

4.3. Multiple neighborhood case

In the experiments for the multi-neighborhoods based schemes we simulate various scenarios of neighborhood formation. In these experiments we increase the number of neighborhoods by decreasing the number of sensors available per neighborhood while keeping the total number of sensors fixed at 60. For example in the first scenario we form 2 neighborhoods with 30 sensors in each of those neighborhoods. In the second scenario 3 neighborhoods are formed with 20 sensors in each of those neighborhoods. Similarly we generated the rest of the scenarios. We generate these scenarios by adjusting the parameters such as transmission range of the sensors.

Classification based on the multiple neighborhoods may arise in various situations. Consider the case in which the transmission range of the sensors is limited to communicate at shorter distances only. It may restrict the sensors to form neighborhoods within their vicinity only. However, this particular situation is favorable for energy conservation [13]. As shown in Fig. 3 performing classification in smaller sized neighborhoods is more efficient in MN-LS scheme. The reason for lesser cost in the multiple neighborhood case is that setting up smaller sized neighborhoods is less expensive in comparison to forming the larger sized neighborhoods. However, in the case of MN-GS scheme the savings from the smaller sized neighborhoods are marginalized by the heavy costs of transmitting the global signatures. As expected communication costs are much higher in MN-GS scheme. These results are presented in Fig. 3b.
The results for classification accuracy in MN-LS and MN-GS schemes are presented in Fig. 4. There is not much dif-

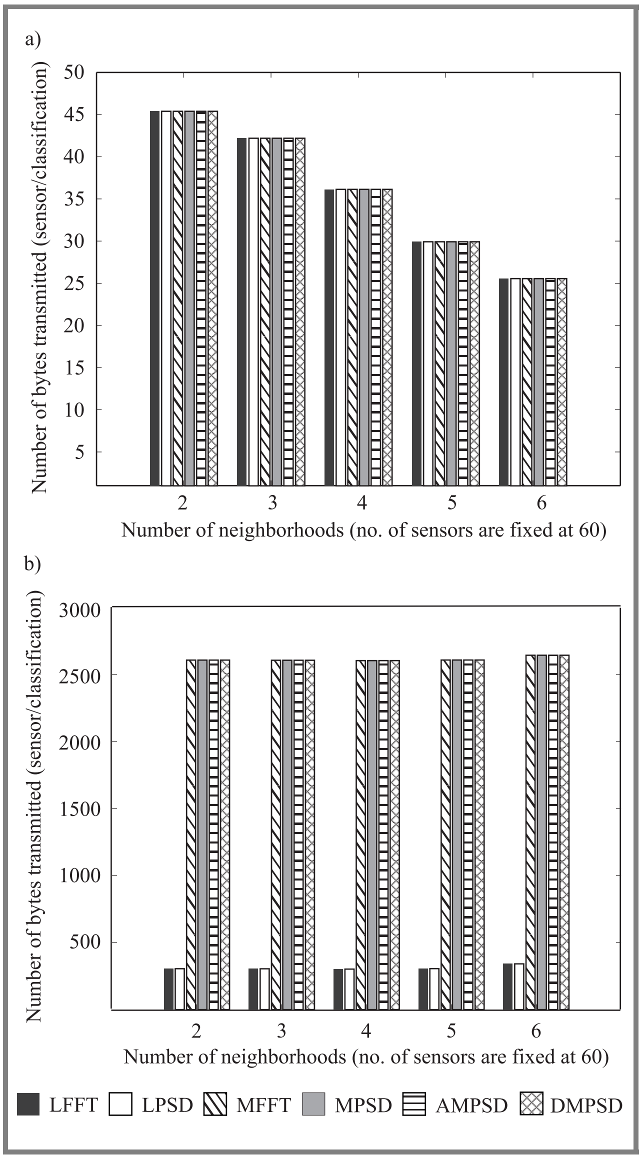

Fig. 3. Communication cost of the multiple neighborhood case: (a) MN-LS; (b) MN-GS.

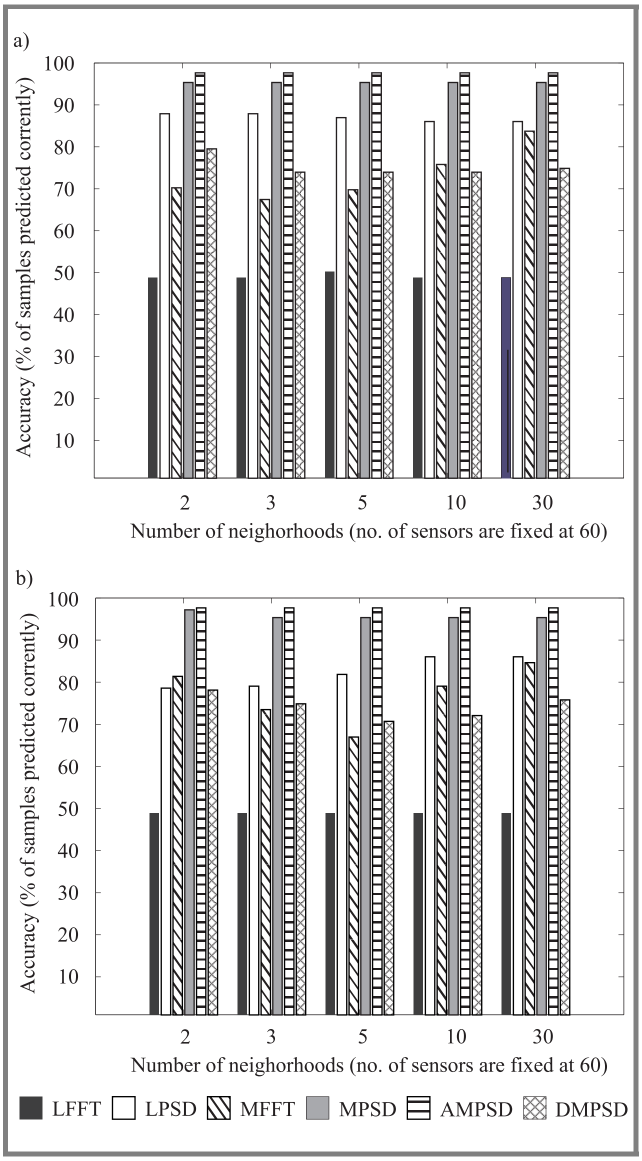

Fig. 4. Classification accuracy of the multiple neighborhood case: (a) MN-LS; (b) MN-GS.

ference between the classification results for single neighborhood scheme (e.g., SN-LS) and multiple neighborhood scheme (e.g., MN-LS) for all features, except DMPSD feature. The accuracy with DMPSD feature decreases as the number of neighborhoods increases. The reason for this behavior is that in the multiple neighborhood schemes the number of sensors per neighborhood decreases. That also means a lesser number of sensors in the neighborhood have the effective features, which affects the overall decision of the neighborhood as a single unit. However, when the number of neighborhoods are large, accuracy improves slightly. In the case of global signatures, a similar trend can be seen in multiple neighborhood schemes for the DMPSD feature. Overall, with a better copy of vehicle's signal available to all participating sensors in a neighborhood, MN-GS scheme performs slightly better than MN-LS.

The results presented here suggest that there is a trade-off between communication costs, computational costs, and achieving a higher classification accuracy. A higher classification accuracy comes at a higher communication and computational costs for sensors. We also note that when the number of training samples are fixed, then varying the number of sensors per neighborhood affects the classification accuracy for some features. Having more sensors in a neighborhood increases the classification accuracy but at a higher cost of communication. On the other hand selection of features is also an important decision. Some features are more expensive to use than others, but their classification results are better. Our proposed DMPSD feature produced the best combination of accuracy and efficiency, respectively, in terms of classification results and computational costs.

5. Conclusions and future directions

Classifying ground vehicles is an important application of wireless sensor networks. Features extracted from the acoustic signatures of these vehicles form the basis for classification. Whether sensor networks provide for efficient implementation of tracking, depends on whether necessary operations, such as classification, can be performed efficiently in a distributed fashion, achieving high classification accuracy at reasonable communication and computational costs. In this paper, we proposed several distributed schemes for vehicle classification. These schemes are based on the idea of collaborations in single and multiple neighborhoods. One distinct contribution of this paper is dynamic acoustic features, which exploit the inherently distributed nature of a sensor network. These features are extracted by the sensors independently of each other in a distributed fashion, which are simple, yet, effective. We conducted a simulation study using real acoustic signals of urban ground vehicles. Simulation results have revealed the performance of our proposed schemes. Our proposed schemes achieved up to 98% accuracy for a binary classification using a naïve classifier. These results are even better than some of the existing results obtained through the k-NN classifier. In the future we would like to improve the efficiency of our proposed schemes. We also plan to conduct an experimental study where we consider more than two classes of ground vehicles.

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