Abstract—It is challenging to classify multiple dynamic targets in wireless sensor networks based on the time-varying and continuous signals. In this paper, multiple ground vehicles passing through a region are observed by audio sensor arrays and efficiently classified. Hidden Markov Model (HMM) is utilized as a framework for classification based on multiple hypothesis testing with maximum likelihood approach. The states in the HMM represent various combinations of vehicles of different types. With a sequence of observations, Viterbi algorithm is used at each sensor node to estimate the most likely sequence of states. This enables efficient local estimation of the number of source targets (vehicles). Then, each sensor node sends the state sequence to a manager node, where a collaborative algorithm fuses the estimates and makes a hard decision on vehicle number and types. The HMM is employed to effectively model the multiple-vehicle classification problem, and simulation results show that the approach can decrease classification error rate.

I. INTRODUCTION

WIRELESS Sensor Network (WSN) is, by definition, a network of sensor nodes that are spread across a geographical area, where each sensor node has a restricted computation capability, memory, wireless communication, and power supply. In general, the objective of WSNs is to monitor, control, or track objects, processes, or events [1]. Fig 3 shows a one cluster of WSN. In WSNs, observed data could be processed at the sensor node itself; distributed over the network; or at the gateway node. Most often, nodes are battery-powered which makes power the most significant constraint in WSNs. The power consumed as a result of the typical data processing tasks executed at the sensor nodes is less than the power consumed for inter-sensor communication. This motivates researches and practitioners to consider decentralized data processing algorithms more than the centralized ones. Multiple-target classification in Multiple moving target classification is a real challenge [2] because of the dynamicity and mobility of targets. The dynamicity of the targets refers to the evolution of the number of targets over time. Furthermore, limited observations, power, computational and communication constraints within and between the sensor nodes make it a more challenging problem. Multiple target classification can be modeled as a Blind Source Separation (BSS) problem [3]. Independent Component Analysis (ICA) can be utilized for such a problem. Most of the recent literature assumes a given number of sources; thus, making the aforementioned challenge easier to solve. Unfortunately, this assumption is unrealistic in many applications of wireless sensor networks. Some recent publications decouple the problem into two sub-problems, namely: the model order estimation problem and the blind source separation problem. Ref.[4] discusses the problem of source estimation in sensor network for multiple target detection. In the literature, many researchers utilized ICA for source separation while others utilized statistical methods as in [5] where the authors presented a particle filtering based approach for multiple vehicle acoustic signals separation in wireless sensor networks. The previously mentioned techniques are based on data fusion. In these techniques, each sensor node detects the targets, extracts the features and sends the data to the manager node. The manager node is responsible for source separation, number estimation, and classification of the sources. The computation and communication overhead induced by such a centralized approaches inadvertently limits the lifetime of the sensor network.

Classification of multiple targets without signals or sources separation based on multiple hypothesis testing is an efficient way of classification [6]. Ref. [7] proposed a distributed classifiers based on modeling each target as a zero mean stationary Gaussian random process and so the mixture signals. A multi hypothesis test based on maximum likelihood is the base of the classifier. In this paper, we are proposing an algorithm to classify multiple dynamic targets based on HMM. HMM decreases the number of hypothesis that is needed to be tested at every classification query. Which decreases the computation overhead. On the other hand, emerging hypothesis transition probability with hypothesis likelihood increases the classification precision. The remainder of this paper is organized as follows. Section 2 formulate the problem mathematically. Section 3 describes modeling the problem as HMM. Simulation environment is described in Section 4. Section 5 presents the results and discussions. And finally conclusions are described in section 6.

II. PROBLEM FORMULATION

Multiple ground vehicles as multiple targets are to be classified in a particular cluster region of a WSN. In this paper, any vehicle that enters the cluster region is assumed to be sensed by all the sensor nodes within this cluster. Each sensor node estimates the number and types of vehicles currently present in the region and the final decision is made
collectively by all the sensor nodes within the region. We assume that the maximum number of distinct vehicles that may exist in one cluster region at the same time $M$ is known. Then the number of hypotheses is $N = 2^M$. The hypotheses correspond to the various possibilities for the presence or absence of different vehicles. Let $h_i$ denote hypothesis $i$, $i = 0, \ldots, N - 1$. Observation $x_t$ is a feature vector obtained by a sensor node at time $k$. The feature vector can be related to the spectrum of a mixture of maximum $M$ vehicle sounds. According to Bayes theorem, $h_i$ is the maximum likelihood hypothesis given $x_t$ if $p(h_i | x_t) > p(h_j | x_t), \forall i \neq j$. So far, the decision about the hypothesis at any given event is based on the observation at that event without any relation with the previous observations as in [7]. In fact, the class to which the feature vector $x_t$ belongs also depends on the previous event class. The classification decision at any instant of time depends on the previous decision and the current observation. Therefore, the classification problem is a context dependent problem and it can be modeled by HMM.

In context-dependant Bayesian classification, a sequence of decisions is needed instead of a single one, and the decisions depend on each other. Let $X = \{x_1, x_2, \ldots, x_t\}$ be a sequence of feature vectors of observations. And let $H_i = \{h_{i1}, h_{i2}, \ldots, h_{it}\}$ be a sequence of classes. According to Bayes theorem, $X$ is classified to $H_i$ if

$$p(H_i | X) > p(H_j | X), \forall i \neq j. \quad (1)$$

$$p(H_i | X)(>)p(H_j | X) \equiv p(X | H_i)p(H_i)(>)p(X | H_j)p(H_j) \quad (2)$$

where $(>)$ denotes comparing and $\equiv$ denotes equivalent to. According to the Markov chain model,

$$p(H_i) = p(h_{i1}) \prod_{k=2}^{N} p(h_{ik} | h_{ik-1}) \quad (3)$$

We assume that $\{x_t\}$ are mutually independent and so are the probability distributions of the classes. Therefore,

$$p(X | H_i) = \prod_{k=1}^{N} p(x_k | h_i) \quad (4)$$

Based on Equ. 2, 3, and 4, we have

$$p(X | H_i)p(H_i) = p(h_{i1})p(x_1 | h_{i1}) \prod_{k=2}^{N} p(h_{ik} | h_{ik-1})p(x_k | h_{ik}) \quad (5)$$

It is computationally expensive to find the maximum value of equation (5) in brute-force task. Thus, Viterbi algorithm is appropriate to solve such a problem of HMM. Given a sequence of observation the most likelihood classes is corresponded to the optimal path. We define the cost of transition from hypothesis $h_{ik}$ to hypothesis $h_{ik-1}$ as $d(h_{ik}, h_{ik-1})$

$$d(h_{ik}, h_{ik-1}) = p(h_{ik} | h_{ik-1})p(x_k | h_{ik}) \quad (6)$$

$$d(h_{i1}, h_{i1}) = p(h_{i1})p(x_1 | h_{i1}) \quad (7)$$

Feature vector of observation of each class $i$ is modeled as a multi variate normal distribution with mean and covariance matrix known. The maximum cost corresponds to the optimal path. The hypotheses along the optimal path result in the observation sequence $X$. Based on Bellman’s principle the cost in Equations (6) and (7) can be computed online.

III. HIDDEN MARKOV MODEL

HMM has a specific discrete number of unobserved states, each state has a transition probability to any other state and an initial probability. The last parameter of HMM is the probability density function of the observation for each state. The state parameters of the HMM are the numbers of targets of each class. For instance, if we have two classes and the maximum number of sources that can be sensed by any sensor at any instant of time is three, then the number of states are eight if the targets are distinct, and ten if not distinct as in Fig. 1. T, W, and 0 represent class T, class W, and no vehicle respectively. Each state represents the number of targets for each class. For instance state TTW means that there are two targets of class T and one target of class W. We assume that the states are equiprobable. This assumption is a reasonable one since it will be the worst scenario compared to trained ones. This means that the state transition probabilities will be equal for all possible states as in Table I. Therefor the initial probabilities are as follows

$$P_1(00T) = P_1(00W) = P_1(000) = \frac{1}{3}$$

Other states initial probabilities are zeros, since we assume that there will one change at a time. Which means that the vehicles enter and exit from the sensor range in a dynamic manner. So the sensor observe one vehicle or nothing at time zero then it goes to possible states as in Fig. 1. This assumption is reasonable because it will approach to the right hypothesis even two vehicles or more enter the sensor range at the same time. It misclassifies it in the first step as one of the initial sates, but it will classify it correctly in the second step. Such cases have a very low probabilities. All of the above contributes in decreasing the computation overhead for multiple hypothesis testing, because the only hypotheses that need to be tested depend on the transition probabilities. So there is no need to test a hypothesis that has zero transition probability. The important parameter of HMM is the output probability density function of each state. This distribution is assumed as a multi variate normal distribution with mean and covariance matrix that are estimated based on maximum likelihood. Mixture of different sources is generated by simulation. The maximum of Equations (6) for all hypothesis at every stage is the maximin likelihood hypothesis. Simulation results show that the correct classification error based on our solution is less than classification with maximum likelihood without modeling the problem as a context dependant classification problem.

IV. SIMULATION ENVIRONMENT

We developed our simulation environment using Matlab for one network cluster region \((300 \times 300)\) as in Fig. 2.
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Where this cluster is consist of a grid of different numbers of sensor nodes. Sensing range for all sensor nodes will be the same. Sensing range is chosen to enable all sensor nodes in one cluster region to observe the same targets with different attenuation. The sensing range is represented by a radius of a circle. When any target enter this circle, the simulator will pick a random real life vehicle sound according to the vehicle type. Where the vehicle type and number are chosen randomly. Then this sound will be attenuated based on the distance between the target and the sensor node. After that, a mixture is linearly formed based on the number of targets. Then each sensor node extracts the feature from the acoustic signal based on discrete spectrum. This mixture is classified by each sensor node. Classification decision is sent to the manger node where decision fusion will be accomplished. Sensor nodes are deployed uniformity as in Fig.2. Simulator is built such that multiple targets can enter the region of simulation from one direction. Entry location and angle are selected randomly. Targets speed and directions are modeled according to Gauss-Markov mobility model. Gauss-Markov mobility model parameters are chosen such that to avoid sharp updates in speed and direction.

Each sensor node calculates the maximum likelihood state based on HMM at every discrete time $t$. State transition cost as in equation (6) is calculated only for states that have nonzero transition probability as in Fig.1 then the maximum of all cost is corresponded to the maximum likelihood state or hypothesis.

V. RESULTS AND DISCUSSIONS

Results, in this paper, are based on simulation with real life vehicle sounds that is available at http://www.ece.wisc.edu/sensit. Fig.4 displays the result of running the simulator hundreds of times. Our experiment is conducted for two distinct vehicles. Simulation results are shown in Fig.4 shows that the correct classification error rate is declining with the sensor density in both cases with and without HMM. It is clear that this error is less in the case of HMM framework. Results are based on majority voting distributed algorithm for all the sensors local decisions in the region of interest. All sensors observe the same number at any instant of time with different attenuation factors. Fig.4 shows how efficient it is to model such kind of problem using HMM and solve it by Viterbi algorithm. HMM based classification approach reduces the computation overhead for multiple hypothesis testing because the only hypotheses that need to be tested are the ones that have not zero state transition probability. For
distinct targets, the number of hypothesis are $2^M$ where $M$ is the maximum number of targets that can be exist within the sensor range at the same time. In our approach only $M + 1$ hypothesis need to be tested at each time step.

VI. CONCLUSIONS

In this paper, we propose an idea of modeling a distributed multiple hypothesis classification problem by HMM. Classification of multiple dynamic vehicles in WSNs can be modeled as a context dependant classification problem. The number of moving vehicles of each class is considered as the state, and each state depends on the previous state. This makes it appropriate to model the system with HMM. Given a sequence of observation, Viterbi algorithm is used to find the maximum likelihood sequence of states. Simulation results based on real vehicle sounds show that using HMM framework decreases the classification error rate. The other benefit of HMM is the reduction of the computation overhead for multiple hypothesis testing. The only hypotheses that need to be tested depend on the state transition probabilities, therefore the hypotheses that need to be tested are the ones that have none zero transition probabilities.

REFERENCES