AISS for Road Anomaly Detection using WSN-Based Distributed Strategy

Goutam Kumar Sahoo[*,1], Saurav Gupta[**,2], Poonam Singh [*,3] and Santos Kumar Das [*,4]
[*]Department of Electronics and Communication Engineering, National Institute of Technology, Rourkela, India
[**]Department of Electronics and Communication Engineering, VR Siddhartha Enginnering College, Vijayawada, India
Email: [1]goutamkrsahoo@gmail.com, [2]greater.saurav@gmail.com, [3]psingh@nitrkl.ac.in, [4]dassk@nitrkl.ac.in

Abstract—With rapid climb in the number of vehicles, it is difficult to deal with traffic issues such as traffic congestion, road anomaly, and vehicle parking. Road anomaly, mainly caused due to accident, is one of the major risk factors in our day-to-day life. Although traditional ways to manage this traffic issue are quite prevalent, yet can be improved with the usage of intelligent and advanced technologies. This will give rise to a smart way of traffic management and can control the anomaly after detecting it in real-time. In this article, a wireless sensor network (WSN)-based automatic information sharing system (AISS) is developed to smartly tackle the above-mentioned issue in a distributed manner. This paper also discusses a hibernate-and-share strategy (HSS) which is employed in WSN to cooperatively find the parameters of interest. It utilizes alternating direction method of multipliers (ADMM) based least-mean-squares (LMS) algorithm to optimally solve the global objective function in a distributed fashion. Simulations are carried-out for the estimation of optimal weights correspond to road anomaly. The results obtained signify the efficient performance of the developed algorithm.

Keywords—Intelligent transport system (ITS), wireless sensor networks (WSNs), automatic information sharing system (AISS), hibernate-and-share strategy (HSS), alternating direction method of multipliers (ADMM).

I. Introduction

Road anomaly[1] is an unpredicted and unintentional event which cannot be completely ignored, but can be reduced to some extent. Many a time, victim may lack intelligent communication system to share information for immediate help. This causes a number of fatalities while meeting with accidents. Therefore, there is a need to develop an automatic information sharing system (AISS) which can automatically detect the road anomaly and share the information for fast response. AISS consists of distributed sensor nodes forming a wireless sensor network (WSN). It is embedded with advanced micro-electromechanical systems for detecting any spatially occurred event. Each node in the network acquires the spatio-temporal data and collaboratively estimate the road anomaly caused due to accident. The recent trend of using WSNs in the field of system identification, anomaly detection, and intelligent transport system (ITS) [1]–[4], leads the motivation of this work. The WSN-based AISS can be installed in the accidental prone areas for providing intelligent infrastructure and may reduce the number of deaths caused during accidents.

Previously, many works have been reported in the literature where data acquired using wireless sensors are processed to detect the road anomaly. In [5], a model is presented to detect the anomaly in non-stationary environment, where WSNs formed by neighboring sensor nodes analyze the data and classify it as normal or anomaly. However, the performance improvement is needed to adopt the changes occurring during data distribution.

In [6], a surveillance and communication based technique is presented for vehicle safety applications like tracking and reporting. Traditional fixed surveillance system along with in-vehicle video camera enhances the safety, however varying light conditions and night time visibility create problem in executing it. In [7], a system is developed by deploying a set of microphones on one side of the road for detecting the accident status such as tire skidding and car crashes from captured sound data. The system works both day and night with illumination variation, however open environment noise increases difficulty in the detection process.

In [4], a wireless communication environment is formed with series of speed sensors installed along a street to get final prediction on real-time collisions. This scheme is evaluated on data-sets collected from a single street, however multiple streets with intersections are not considered. In [8], sensor based techniques are presented to address the issues of traffic accident. The solution of fixed traffic sensors installation in all roads are expensive. However, installation of mobile traffic sensors in vehicles reduces the cost, but fast processing of large volume of mobile sensor's data are the main issue.

In [9], an automatic incident detection method based on car traffic data is presented to detect the abnormal movement of vehicle. It provides the details of location with time-stamp, speed and direction. This method is not suitable for local streets, where cars stop frequently under normal circumstances. In [10], a survey is presented on application of WSNs to ITS to provide a cost-effective solution for traffic control and safety. The information produce by sensor nodes is transmitted for centralized processing at traffic management center. The large data

[1]Road anomaly in this article refers to the road accident.

of sensor nodes suffers from transmission delay and require robust communication infrastructure which is costly.

In centralized method, the processing and decision making of sensor data occurs at fusion-center (FC) but it has certain drawbacks such as

1) inefficient to establish multi-hop communication between sensor nodes and FC, considering energy consumption and communication bandwidth [11],
2) highly reliable and robust central processing device is required to support the processing of large amount of data generated in real-time [12],
3) when FC fails the whole system networking breaks, which makes the system non-robust [13], [14].

The above limitations can be overcome using distributed techniques which are of often used with various practical applications [13], [15]. In the literature, all the works have been carried out using centralized method which has certain limitations as discussed above. This paper suppresses these limitations using distributed strategy over wireless sensor networks, at the same time maintaining a decent accuracy. This strategy can process a large amount of data in real-time which is very much suitable for ITS. It involves the local processing of data at each sensor node and then exchanging the information with the neighboring nodes to find global optimal weights of anomaly caused due to accident. There are three general types of distributed strategies to estimate the required parameters: incremental, diffusion, and consensus (average consensus, alternating direction method of multipliers (ADMM) consensus, etc.). The drawback concerning the incremental strategy is that if any nodes or links get failed whole system breaks-down. The diffusion strategy has slow convergence rate compare to ADMM consensus. In [16], ADMM strategy is used to estimate the required parameters in a distributed manner. Hence, ADMM-based consensus is of considerable interest in this article.

This article develops an ADMM-based distributed least-mean-squares (LMS) adaptive estimation scheme for real-time detection of road anomaly. It is used as an AISS which has the the advantage of being simple to implement with decent accuracy. This scheme will foster the development of smart cities by timely informing the nearest helping source for providing the first-aid to the accident victim. It involves the idea of hibernate-and-share strategy (HSS) where nodes will share the information to their neighbor nodes only when some abnormality is detected. When no abnormality occurs, nodes are assumed to be in hibernate state. Hibernate in this discussion refers to a stand-by-state in which the nodes are capable of sensing the normal road activity but do not share them to their neighboring nodes. The nodes in the network cooperatively detect the anomaly caused due to accident. HSS requires the uniform deployment of nodes in the accident prone zone. These nodes are generally fixed within the roadway infrastructure (such as side walls, traffic lights, street lamp post, etc.) to gather the information.

The remaining parts of the article is organized as follows. Section II presents the problem definition and the description of distributed detection algorithm is given in Section III. Section IV discusses the simulation results and the conclusive remarks is provided in Section V.

II. Problem Definition

In this work, we assume that the accident has been occurred which results the anomaly on the road surface. Let say, accident is occurred in the common region covered by the nodes $k-1$, k, $k+1$, and j as shown in Fig.1. The nodes nearer to the accident spot will act

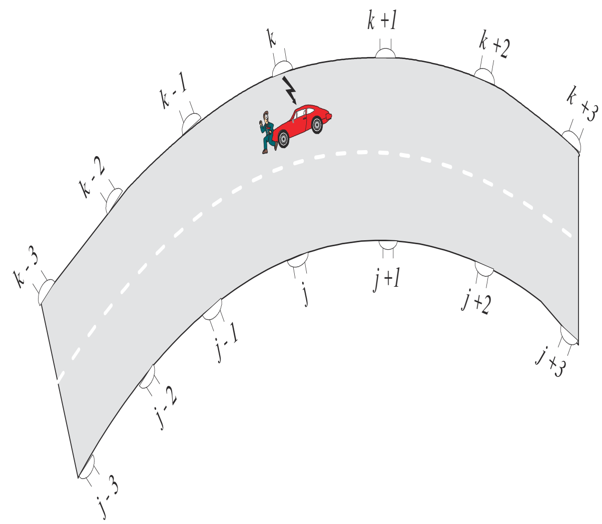

Fig. 1: Sensor nodes deployment across the road.

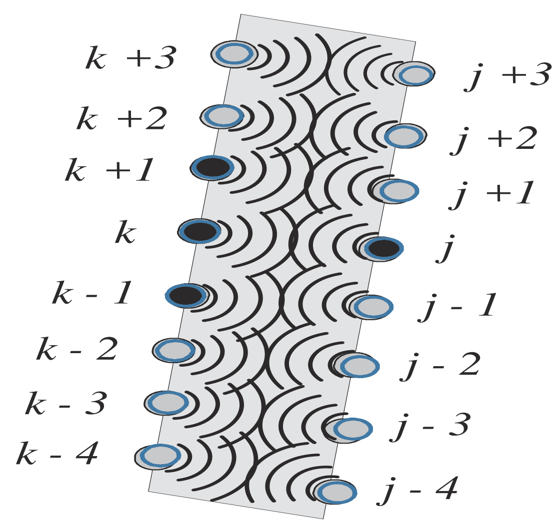

Fig. 2: Cover range of sensor nodes.

as master nodes (MNs) that will together form a sub-network to detect anomaly across the road. Practically, the MN has the ability to share the information with the nodes coming under its coverage area. The nodes that involve in the process of information sharing with MN are considered to be its neighbors. Each MN will broadcast its information and try to communicate with the nodes in its neighborhood. The neighbor nodes that are initially at hibernate stage will start taking part in the sharing process. Let any MN (say k) has the covering area consisting of uniformly distributed single-hop forward and backward nodes. Hence, MN k will transmits the gathered information to its immediate adjacent nodes $k-1$ and $k+1$ as well as j^{th} node as it is in the its coverage area shown in Fig. 2. Then these nodes will transmit their information to their next immediate nodes for emergency indication. The overall strategy can be implemented with the powerful optimization technique known as ADMM [17]–[19]. It cooperatively solves the global cost function by separating it into multiple sub-tasks. Each sub-task belongs to any of the individual nodes in the network.

III. HSS-Based Distributed LMS Algorithm

It is assumed that HSS with MN form a connected sub-network. Whenever accident occurred, the MNs of the sub-network on either side of lane start sharing the information. The objective is to develop an accident detection algorithm which will have advanced features to handle sensor data (received from the moving vehicles) of different formats, i.e. data with missing values, data corrupted by noise, etc. These data can be analyzed to take decision on the occurrence of accident within a short time period and can suggest nearby vehicles to take alternate route to avoid congestion. It will be very much difficult and expensive considering power consumption, communication bandwidth requirement to collect the raw data from all roads and process them in a real time. Hence, a flexible and distributed processing is adopted to manage high volume of data and to address the real time problems.

Let us consider a single lane road (in the accident prone zone) whose both sides are deployed with sensor nodes. These nodes are uniformly placed throughout the road. It is assumed that any node i obtains its observations using a linear regression model [20]

$$a_i\left(t\right) = \bar{w}_{opt}^T \bar{u}_i\left(t\right) + v_i\left(t\right) \tag{1}$$

where $\bar{w}_{opt} \in \mathbb{R}^M$ is the optimal weight vector of the system under consideration (geographical system where accident took place). $\bar{u}_i(t) \in \mathbb{R}^M$ and $a_i(t) \in \mathbb{R}$ are the input and output of the i^{th} node, respectively, at any time instant t. $v_i(t)$ is the observational noise that is considered to be of Gaussian nature with mean zero and driving variance σ_i^2. Let P number of MNs form a wireless subnetwork to detect the anomaly occurred. All the input vectors of MNs are stacked to form a global matrix $\boldsymbol{U}\left(t\right) = \left[\bar{u}_1\left(t\right), ..., \bar{u}_P\left(t\right)\right] \in \mathbb{R}^{M\times P}$ and their corresponding scalar outputs are stacked as global vector $\bar{A}\left(t\right) = \left[a_1\left(t\right), ..., a_P\left(t\right)\right]^T \in \mathbb{R}^{P\times 1}$. The global parameter estimates of $\bar{w}_{opt}$ can be obtained by the minimization of the following quadratic problem

$$\begin{aligned}\hat{\bar{w}}(t) &= \arg\min_{\bar{w}} \mathrm{E}\left\|\bar{A}\left(t\right) - \boldsymbol{U}^T\left(t\right)\bar{w}\right\|^2 \\ &= \arg\min_{\bar{w}} \sum_{i=1}^{P} \mathrm{E}\left[\left(a_i\left(t\right) - \bar{u}_i^T\left(t\right)\bar{w}\right)^2\right],\end{aligned} \tag{2}$$

where, E represents the expected value operator.

The (2) can be optimized by introducing the auxiliary variables of $\bar{w}$ as local variables $\{\bar{w}_i\}_{i=1}^P$, which represents the local estimate of accident model parameters. These auxiliary variables allow splitting of independent task across each sensor nodes, that reforms it as constrained minimization problem given in (3)

$$\begin{gathered}\left\{\hat{\bar{w}}_i\left(t\right)\right\}_{i=1}^P = \arg\min_{\bar{w}_i} \sum_{i=1}^{P} \mathrm{E}\left[\left(a_i\left(t\right) - \bar{u}_i^T\left(t\right)\bar{w}_i\right)^2\right], \\ \text{such that } \ \varepsilon\,\bar{w}_i = \varepsilon\bar{w}_{i'},\ i\in\left[1,P\right],\ i'\in\mathcal{N}_i.\end{gathered} \tag{3}$$

Here, it is assumed that each of the nodes $i \in [1, P]$ exchange its local estimates with all other nodes within its closest neighborhood $i' \in \mathcal{N}_i$. The main objective of this approach is to find the estimates $\bar{w}$ at each node without requiring of the stacking measurements. Then, the output is predicted from the measurement at any node i as

$$\hat{a}_i\left(t\right) = \bar{w}_i^T\left(t\right)\bar{u}_i\left(t\right). \tag{4}$$

The distributed modeling approach does not require the construction of global vector $\bar{A}(t)$. The positive constant ε can be used significantly as error controlling parameter and it has no effect on the consensus constraints.

The distributed solution can be obtained by applying ADMM, where we can add a set of auxiliary variables $\bar{z} = \left\{\bar{z}_i^{i'}\right\}_{i\in[1,P]}^{i'\in\mathcal{N}_i}$ that can be eliminated during the derivation of local update recursions. Hence, the constraints in (3) can be written as

$$\varepsilon\,\bar{w}_i = \varepsilon\,\bar{z}_i^{i'},\ \varepsilon\,\bar{w}_{i'} = \varepsilon\,\bar{z}_{i'}^{i}\quad \forall\, i\in\left[1,P\right],\ i'\in\mathcal{N}_i,\ i\neq i'. \tag{5}$$

The constrained optimization problem is generally handled by the method of Lagrange multipliers [21]. The quadratically augmented Lagrangian function of (3) with the constraints in (5) can be obtained as [19]

$$\begin{aligned}\mathcal{L}_a\left(\bar{w},\bar{z},\bar{\ell},\bar{\gamma}\right) = &\sum_{i=1}^{P} \mathrm{E}\left[\left(a_i\left(t+1\right) - \bar{u}_i^T\left(t+1\right)\bar{w}_i\right)^2\right] \\ &+ \sum_{i=1}^{P}\sum_{i'\in\mathcal{N}_i} \varepsilon\left[\left(\bar{\ell}_i^{i'}\right)^T\left(\bar{w}_i - \bar{z}_i^{i'}\right) + \left(\bar{\gamma}_i^{i'}\right)^T\left(\bar{w}_i - \bar{z}_{i'}^{i}\right)\right] \\ &+ \sum_{i=1}^{P}\sum_{i'\in\mathcal{N}_i} \frac{c_i\varepsilon^2}{2}\left[\left\|\bar{w}_i - \bar{z}_i^{i'}\right\|^2 + \left\|\bar{w}_i - \bar{z}_{i'}^{i}\right\|^2\right],\end{aligned} \tag{6}$$

where, the Lagrange multiplier vectors $\bar{\ell} = \left\{\bar{\ell}_i^{i'}\right\}_{i\in[1,P]}^{i'\in\mathcal{N}_i}$ and $\bar{\gamma} = \left\{\bar{\gamma}_i^{i'}\right\}_{i\in[1,P]}^{i'\in\mathcal{N}_i}$ are the consensus constraints of (5) and c_i represents the positive penalty coefficients w.r.t. to the violation of consensus constraints.

ADMM is applied to solve the augmented Lagrangian function in (6) to obtain the updates of $\{\bar{w}, \bar{\ell}, \bar{\gamma}\}$ at any time t. The steps followed to obtain the ADMM solution are:

1.) The gradient ascent method is used to get the local updates for the Lagrange multipliers as

$$\begin{array}{l} \bar{\ell}_i^{i'}(t) = \bar{\ell}_i^{i'}(t-1) + c_i \varepsilon \left(\bar{w}_i(t) - \bar{z}_i^{i'}(t) \right), \text{ for } i \in [1, P] \\ \text{and } i' \in \mathcal{N}_i. \\ \bar{\gamma}_i^{i'}(t) = \bar{\gamma}_i^{i'}(t-1) + c_i \varepsilon \left(\bar{w}_i(t) - \bar{z}_{i'}^{i}(t) \right), \text{ for } i \in [1, P] \\ \text{and } i' \in \mathcal{N}_i. \end{array} \tag{7}$$

2.) The local estimates of $\bar{w}_i$ at each sensor i is evaluated using the coordinate descent method, where (6) is minimized w.r.t. $\bar{w}_i$ by considering parameters $\left\{ \bar{z}_i^{i'} \right\}_{i \in [1,P]}^{i' \in \mathcal{N}_i}$, $\left\{ \bar{\ell}_i^{i'} \right\}_{i \in [1,P]}^{i' \in \mathcal{N}_i}$ and $\left\{ \bar{\gamma}_i^{i'} \right\}_{i \in [1,P]}^{i' \in \mathcal{N}_i}$ to be fixed,

$$\bar{w}(t+1) = \arg \min_{\bar{w}} \mathcal{L}_a \left(\bar{w}, \bar{z}(t), \bar{\ell}(t), \bar{\gamma}(t) \right). \tag{8}$$

3.) The coordinate descent method is applied to obtain local estimates z_i at each sensor i, where (6) is minimized w.r.t. $\bar{z}_i$ by considering parameters $\{\bar{w}_i\}_{i=1}^{P}$, $\left\{ \bar{\ell}_i^{i'} \right\}_{i \in [1,P]}^{i' \in \mathcal{N}_i}$ and $\left\{ \bar{\gamma}_i^{i'} \right\}_{i \in [1,P]}^{i' \in \mathcal{N}_i}$ to be fixed,

$$\bar{z}_i(t+1) = \arg \min_{\bar{z}} \mathcal{L}_a \left(\bar{w}(t+1), \bar{z}, \bar{\ell}(t), \bar{\gamma}(t) \right). \tag{9}$$

Let's initialize the Lagrange multipliers as $\bar{\ell}_i^{i'}(0) = -\bar{\gamma}_i^{i'}(0)$, and it follows $\bar{\ell}_i^{i'}(t) = -\bar{\gamma}_i^{i'}(t)$, $\forall t$. Now finding the gradient of (6) w.r.t. $\bar{z}_i$ and equating it to zero, the desired results is obtained as,

$$\begin{aligned} &\bar{z}_i^{i'}(t+1) \\ &\quad = \tfrac{1}{2 c_i \varepsilon} \left[\bar{\ell}_i^{i'}(t) + \bar{\gamma}_{i'}^{i}(t) \right] + \tfrac{1}{2} \left[\bar{w}_i(t+1) + \bar{w}_{i'}(t+1) \right] \\ &\quad = \tfrac{1}{2} \left[\bar{w}_i(t+1) + \bar{w}_{i'}(t+1) \right], \;\; i \in \; [1, P], \;\; i' \in \mathcal{N}_i. \end{aligned} \tag{10}$$

Now substituting (10) into (7), we will get

$$\bar{\ell}_i^{i'}(t) = \bar{\ell}_i^{i'}(t-1) + \frac{c_i \varepsilon}{2} \left(\bar{w}_i(t) - \bar{w}_{i'}(t) \right). \tag{11}$$

Now the recursion of $\bar{w}_i$ can be obtained by finding the gradient of (6) w.r.t. $\bar{w}_i$ and equating it to zero as,

$$\begin{aligned} &\mathrm{E} \left[-2 \, \bar{u}_i(t+1) \left(a_i(t+1) - \bar{u}_i^T(t+1) \, \bar{w}_i \right) \right] \\ &\quad + \sum_{i' \in \mathcal{N}_i} \left\{ \begin{array}{l} \varepsilon \left(\bar{\ell}_i^{i'}(t) - \bar{\ell}_{i'}^{i}(t) \right) \\ +2 c_i \varepsilon^2 \left(\bar{w}_i - \frac{1}{2} \left(\bar{w}_i(t) + \bar{w}_{i'}(t) \right) \right) \end{array} \right\} = 0. \end{aligned} \tag{12}$$

The expected value of (12) requires the statistical knowledge of data which is not known in many practical applications. To obtain the local recursions a stochastic approximation is used to update $\bar{w}_i$ as,

$$\begin{aligned} &\bar{w}_i(t+1) = \bar{w}_i(t) + \\ &\mu_i \left[\begin{array}{c} 2 \, \bar{u}_i(t+1) \, e_i(t+1) - \sum_{i' \in \mathcal{N}_i} \varepsilon \left(\bar{\ell}_i^{i'}(t) - \bar{\ell}_{i'}^{i}(t) \right) \\ - \sum_{i' \in \mathcal{N}_i} c_i \varepsilon^2 \left(\bar{w}_i(t) - \bar{w}_{i'}(t) \right) \end{array} \right], \end{aligned} \tag{13}$$

where, $e_i(t+1) = \left(a_i(t+1) - \bar{u}_i^T(t+1) \, \bar{w}_i \right)$ and μ_i is the step size.

The algorithm 1 used to identify the distributed parameters of accident detection model through WSNs involves local recursions (11) and (13). The robustness of the algorithm is improved by performing both the recursions at every node.

Algorithm 1 HSS based distributed LMS algorithm

At any time instant $t = 0$, for nodes $i = 1, .., P$, Initialize $\bar{l}_i^{i'}(t)$ and $\bar{w}_i(t)$ as random vector.
for $t = 1, 2, \ldots$ do
  for $i = 1, 2, .., P$. do
    Update $\bar{\boldsymbol{l}}_i^{i'}(t)$ using (11) for $i' \in \mathcal{N}_i$ and $i \neq i'$
    Update $\bar{\boldsymbol{w}}_i(t)$ using (13)
  end
Predicted output $\hat{a}_i(t) = \bar{w}_i^T(t) \, \bar{u}_i(t)$ using (4)
end.

IV. Result discussion

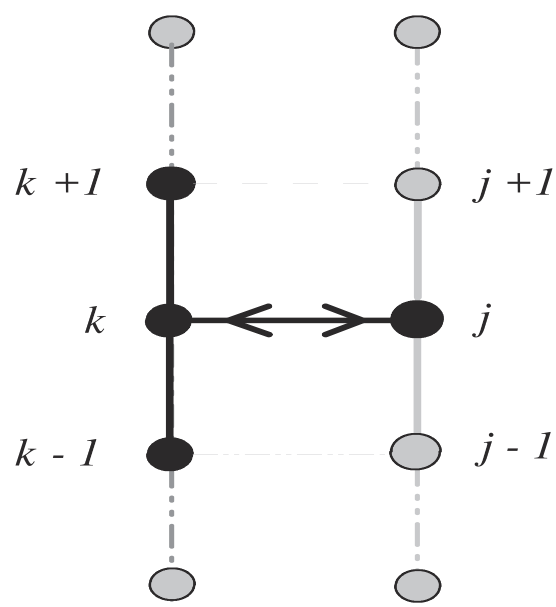

Fig. 3: Wireless network formed through MNs.

Consider a wireless network formed through four-MNs ($k-1$, k, $k+1$, and j) which are taking part in the road anomaly detection as shown in Fig. 3. Rest other nodes are in the hibernate state. All the four MNs locally estimates the anomaly weight vector (w_{opt}) using the measured input-output data $(\bar{u}(t),\ a(t))$. Each node will share the local estimates with its neighbor nodes. One can observe from Fig. 3 the neighbors of $k-1,\ k+1,$ and j. Similarly, the neighborhood of $k-1$ is the node k, and so on.

The measured input $\bar{u}_i(t) \in \mathbb{R}^{M=4}$ at any node i, at any time t is considered to be of Gaussian in nature with zero mean and unit variance. The corresponding scalar measured output $a_i(t)$ can be obtained using (1) with $\bar{w}_{opt} = [0.5 \quad 0.2 \quad 0.6 \quad 1]^T$ and noise variances σ_i^2. The global cost to estimate $\bar{w}_{opt}$ is collaboratively optimized using the recursions (11) and (13).

The developed algorithm is evaluated based on performance parameters the mean-square deviation (MSD) and excess mean-square error (EMSE). These quantities at any node i can be defined as

$$MSD_i(t) = \mathrm{E}\left\|\bar{w}_{opt} - \hat{\bar{w}}_i(t)\right\|^2,$$

$$EMSE_i(t) = \mathrm{E}\left|\bar{u}_i^T(t)\left(\bar{w}_{opt} - \hat{\bar{w}}_i(t)\right)\right|^2.$$

The performance of the network at any instant $'t'$ is obtained by performing the average of all other nodes performances as

$$MSD^{network}(t) \triangleq \frac{1}{P}\sum_{i=1}^{P} MSD_i(t),$$

$$EMSE^{network}(t) \triangleq \frac{1}{P}\sum_{i=1}^{P} EMSE_i(t),$$

where in this particular case, $P = 4$ is used as number of MNs are 4.

The performance curves of both centralized and distributed techniques are obtained for $\mu = 0.01$ and 0.05 with $c = 10^{-7}$, $\varepsilon = 1$ and $\sigma^2 = 10^{-4}$. These are taken to be constant at each nodes (MNs) taking part in detection. From the simulation curves plotted in Fig. 4, it can be observed that the steady-state error is very less. The performance parameter MSD and EMSE are calculated with the step size of $\mu = 0.01$ and 0.05 for both the techniques (centralized and distributed). In centralized method, MSD is found to be $-57dB$ and $-49dB$ where as for distributed technique it is $-53dB$ and $-46dB$ for $\mu = 0.01$ and 0.05, respectively. Similarly EMSE, in centralized method is found to be $-57dB$ and $-49.5dB$ where as for distributed technique it is $-52.5dB$ and $-45dB$ for $\mu = 0.01$ and 0.05, respectively. The performance curves of the proposed distributed technique are quite close to the centralized technique which is the benchmark for validation of proposed algorithm. Hence, the algorithm can be effectively used to obtain the road anomaly weight vector. The speed of algorithm detection depends mainly on the step-size μ. If μ increases, the accuracy decreases by some extent but at the same time speed of convergence increases which can be observed from the performance curves. So, there is a trade-off between accuracy and step-size. Both have to be chosen in such a way that meets with the required performance.

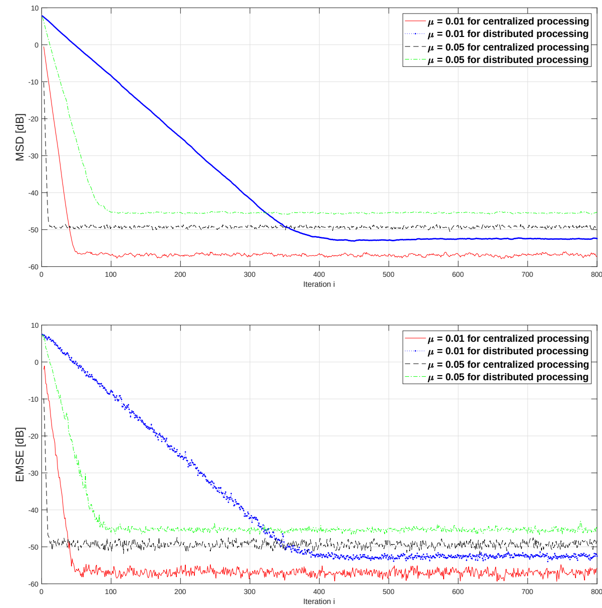

Fig. 4: Overall network performance comparison curves.

V. Conclusive Remarks

This article has presented a road anomaly detection algorithm where sensor nodes are deployed across the road. This algorithm is based on the idea of HSS as described earlier under Section III. Once the anomaly occurred on the road, the nodes nearer to the source called MNs, form a connected network. This network utilizes the in-network LMS-based distributed strategy to on-line estimate the required parameters. After estimation of the parameters, each MN shares information to its immediate neighbors for signaling the upcoming vehicles about entering in the danger zone. The simulation results have been obtained in the presence of noisy environment that demonstrate the algorithm's ability to detect any anomaly across the road. In future, the real-data can be used to validate the algorithm. Also, the algorithm can be made energy-efficient which helps in longer-life of the deployed sensors.

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