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Acoustic Signature Identification Using Distributed Diffusion Adaptive Networks

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Abstract—In this paper, we propose using distributed diffusion adaptive networks for acoustic signature identification, as a time-varying autoregressive (TVAR) stochastic model. A distributed adaptive sensor network considers spatio-temporal challenges simultaneously. To analyze diffusion networks under TVAR modeling problem circumstances, we investigate and elaborate on their performance under non-stationary conditions. Different versions of diffusion networks are then theoretically compared under the problem conditions. Furthermore, their superiority to single point observations is shown. Finally, the proposed algorithms are implemented on a raw and real sensor network dataset recorded from moving vehicles. The experimental results well support the theoretical findings, and demonstrate the excellence and efficacy of distributed diffusion adaptive networks for this case.

Keywords—Acoustic signature identification; TVAR modelling; Adaptive networks; Diffusion LMS; Distributed estimation.

I. INTRODUCTION

An acoustic signature contains a considerable amount of information about its source. This information can be used for variety of applications including source classification, detection, and tracking [1], [2]. Also, source localization and motion parameter estimation are possible using acoustic sensors [3], [4]. Having passive, low-cost, deployable nature as well as being low-power, make the acoustic sensors an unsurpassed choice for surveillance applications for both ground and air vehicles.

Autoregressive (AR) modelling, as a parametric method, is a well-known solution for extracting acoustic signature. While the AR model is well-fitted to stationary signals, the practical acoustic signals are always seen to be of non-stationary nature. The non-stationarity usually arises from source and environment spatio-temporal variations. To increase the accuracy and reliability, non-stationary nature is considered defining a Time-Varying Autoregressive model (TVAR) [5].

Since the acoustic signal propagates over a geographical region, physically, every fixed point observes the process with a limited quality. Moreover, source movements do add more complexity to this problem. To deal with this challenge, multiple observations should be involved in the modeling procedure. If a more comprehensive estimation is desired to be obtained by merging multiple observations, a sensor network thus needs to be implemented, in which some of the nodes are linked together. Nodes are allowed to cooperate with each other, mostly through wireless links. Adaptive network which was first introduced in [6] is a general model that is

capable of being fitted to sensor networks. In this paradigm, adaptive filters are networked together to estimate an unknown parameter. Adaptive networks are divided into two main categories from the topology point of view, incremental and diffusion. Incremental adaptive networks cycle the network in a Hamiltonian path, where each adaptation step needs a full cycle [7]. Although a full cycle in each adaptation step gives an overall result, finding a Hamiltonian path, susceptibility to node and link failure, and time-consuming adaptation step are some serious obstacles for this topology. In diffusion topology, every node prepares a local estimation consulting with its adjacent nodes only [8], addressing the increment's drawbacks with a reasonable trade-off.

In this research, we propose employing a diffusion adaptive network for acoustic signature identification problem. Considering a TVAR model for the acoustic signal, the adaptive network solve the spatio-temporal problem simultaneously. In one side, we regard both adapt-then-combine (ATC) and combine-then-adapt (CTA) versions and in other side a simple algorithm based on individual estimations is considered. The performance of the proposed methods are compared in terms of the network steady-state mean-square deviation (MSD) and excess mean-square error (EMSE). Since the diffusion networks have to work under non-stationary conditions, the error criteria should be extracted under these conditions. The performance of diffusion adaptive network is concisely investigated in [7] aimed at information exchange version only and various diffusion algorithms errors were neither obtained nor compared. In this research, we investigate and elaborate on diffusion adaptive networks performances without information exchange. Network steady-state MSD and EMSE are extracted for different versions and they are also compared in TVAR model identification problem. By proposing diffusion adaptive networks for acoustic signature identification, we investigate the theoretical results and implement the methods on a real dataset. It is worth noting, while the adaptive networks have been proposed for a decade, they have not been implemented on any raw data so far. We use the data collected in situational experiment (SITEX02), organized by DARPA/IXOs SensIT (Sensor Information Technology) program.

This paper is organized as follows. The TVAR model for acoustic signature identification is expressed in Section II. Employing diffusion adaptive networks is proposed in Section III. In Section IV diffusion adaptive networks are

investigated under non-stationary conditions and compared in TVAR case. Finally, in Section V, the proposed algorithms are implemented on the real recorded acoustic data from moving vehicles.

II. PROBLEM FORMULATION

Using TVAR model for acoustic signals to consider non-stationary nature is a well-known approach [5], [9]. A TVAR model with order p is expressed for a non-stationary signal as follows:

$$x(n) = -\sum_{k=1}^p a_i(k)x(n-k) + u(n) \quad (1)$$

where the current value of signal $x(n)$, is a weighted sum of the previous values biased by a driving sequence $u(n)$. The driving sequence is assumed to be a zero-mean Gaussian process. The assessment in this model is associated with the estimation of model's parameter, $a_i(k)$, which determines the weights of the summation. In this equation, the model's parameter is allowed to change with time i . In adaptive solution, a dynamic model is regraded for the time-varying parameter and is constructed based on an adaptive filter which takes the advantages of self-tuning feature .

In considerable variety of practical applications we are confronted with real-time challenges, wherein the parameters should be estimated online. In these cases, providing instantaneous value of parameters based on last inputs and outputs, adaptive methods demonstrate an unsurpassed performance. Apart from sensitivity of adaptive procedures to noise, their online feature is convincing enough to apply them for real-time model identification. Moreover, adaptive methods have a strong mathematical support where their strengths and weaknesses are predictable. In this paper, we focus on adaptive solution and analyze the model in a networked form.

Assuming a_i as a vector consisting of the unknown parameters, the dynamic model is expressed as follows:

$$a_i = a_{i-1} + \nabla a_i$$

where ∇a_i represents the innovation term, which could be different based on the applied adaptation rule. For instance, if LMS rule is employed, the recursion is formulated as follows:

$$\begin{aligned} \hat{a}_{p,i} &= \hat{a}_{p,i-1} + \mu x_{p,i}^* e(i) \\ x_{p,i} &= [x(i-1), x(i-2), \dots, x(i-p)] \\ e(i) &= x(i) - x_{p,i} \hat{a}_{p,i} \end{aligned}$$

where, μ is the adaptation step or learning rate, $x_{p,i}$ is a vector containing the last p measurements and $e(i)$ denotes the estimation error. Using this adaptation rule, an adaptive filter estimates the unknown vector.

III. TVAR MODEL IDENTIFICATION USING DIFFUSION ADAPTIVE NETWORKS

The process is propagated over a geographical region in some occasions and such distribution leads to spatial variations, as well. In these circumstances, relying only on a

single point's observations leads to a rudimentary estimation. Hence, for spatio-temporal analysis, sensor networks should be employed.

Consider a set of N sensor nodes dispersed in a geographical region measuring a particular parameter of a random process. At each time instant, every node (k), collects a scalar measurement ($\mathbf{d}_k(i)$) and a regressor vector ($\mathbf{u}_{k,i}$) while these two measured quantities are assumed to be linearly related through an unknown vector, w° . It is also assumed that the observed quantities are corrupted by an additive noise ($\mathbf{v}_k(i)$) through a conventional linear regressor model, thus:

$$\mathbf{d}_k(i) = \mathbf{u}_{k,i} w^\circ + \mathbf{v}_k(i), \quad k = 1, \dots, N \quad (2)$$

The general objective in adaptive networks is to estimate the optimal vector, w° that minimizes the mean-square error (MSE):

$$w^\circ = \underset{w}{\operatorname{argmin}} \frac{1}{N} \sum_{k=1}^N \mathbb{E} |\mathbf{d}_k - \mathbf{u}_k w|^2 \quad (3)$$

An adaptive network is formed by N networked adaptive filters cooperating with each other to solve the estimation problems. Distributed diffused plan was proposed as a solution in [10]. In this method, each node uses information of all of the adjacent nodes. For this purpose, node k makes local combination (i.e., $\psi_{k,i-1}$) of all the neighbouring nodes . This combination can be expressed by the following equation:

$$\psi_{k,i-1} = \sum_{\ell \in \mathcal{N}_k} a_{k,\ell} \phi_{\ell,i} \quad (4)$$

where $\phi_{\ell,i}$ is an individual estimation in node l and iteration i . ℓ represents the set of neighboring nodes (including node k itself), and $a_{k,\ell}$ denotes the coefficients used to combine adjacent individual estimations . This technique is summarized in Algorithm 1, wherein the adaptation step is followed by combination step (adapt-then-combine (ATC)). The combination and adaptation steps can be swapped. In this case, combine-then-adapt (CTA) version of diffusion strategy is employed [8].

A primitive adaptive solution is employing individual adaptive nodes whereby the network and cooperation are negated. Expectedly, this mode will not prepare a comprehensive estimation since the nodes do not consult with each other. If we are aimed at investigating the efficiency of adaptive networks, obviously, the performance should be compared with no-cooperation algorithm.

Algorithm 1 Distributed LMS diffusion ATC [8]

Start with an initial estimate, $\phi_{\ell,-1}$:

In each iteration $i \geq 0$:

For each node k :

1: Adapt local estimation:

$$\phi_{k,i} = \psi_{k,i-1} + \mu_k u_{k,i}^* (d_k(i) - u_{k,i} \psi_{k,i-1})$$

2: Combine local estimations:

$$\psi_{k,i} = \sum_{\ell \in \mathcal{N}_k} a_{k,\ell} \phi_{\ell,i}$$

IV. PERFORMANCE ANALYSIS

To commence the analysis, we should consider some assumptions both in data and the unknown parameter. Since we are studying the diffusion networks under non-stationary conditions, we use the random walk model to consider time variations. Parameter vector varies based on the following model:

$$\mathbf{w}_i^\circ = \mathbf{w}_{i-1}^\circ + \boldsymbol{\eta}_i$$

where \mathbf{w}_{i-1} is a random variable with constant mean and $\boldsymbol{\eta}_i$ is a zero-mean random sequence with covariance matrix $R_{\boldsymbol{\eta}}$. The following assumption is taken for data model:

Assumption 4.1 (Data model):

The unknown vector, \mathbf{w}_i° is related to \mathbf{d} and \mathbf{u} as follows:

$$\mathbf{d}_k = \mathbf{u}_k \mathbf{w}_i^\circ + \mathbf{v}_k \quad (5)$$

where \mathbf{v}_k denotes white noise with variance σ^2 and independent of $\{\mathbf{d}_l, \mathbf{u}_l\}$ for all l s.

- 1) \mathbf{u}_k is independent of \mathbf{u}_l for $k \neq l$ (spatial independence).
- 2) For every k , the sequence \mathbf{u}_k is independent over time (time independence).
- 3) The regressors \mathbf{u}_k are produced from a source with circular Gaussian distribution with covariance matrix $R_{\mathbf{u},k}$.
- 4) The weight vector varies according to random walk model.
- 5) The sequence $\boldsymbol{\eta}_i$ is independent of $\mathbf{u}_{k,j}$ and $\mathbf{v}_k(j)$ for all i and j .
- 6) The initial conditions $\mathbf{w}_{-1}^\circ, \mathbf{w}_{k,-1}$ are independent of all $\mathbf{d}_i, \mathbf{u}_i, \mathbf{v}_i$ and $\boldsymbol{\eta}_i$.

To aggregate the analysis of different types of diffusion mode, we had better deal with a general diffusion adaptive solution [11]:

$$\begin{aligned} \phi_{k,i-1} &= \sum_{\ell \in \mathcal{N}_k} a_{1,\ell k} \mathbf{w}_{\ell,i-1} \\ \psi_{k,i} &= \phi_{k,i-1} + \mu_k \mathbf{u}_{k,i}^* [\mathbf{d}_k(i) - \mathbf{u}_{k,i} \phi_{k,i-1}] \\ \mathbf{w}_{k,i} &= \sum_{\ell \in \mathcal{N}_k} a_{2,\ell k} \psi_{\ell,i} \end{aligned} \quad (6)$$

where $\{a_{1,\ell k}, a_{2,\ell k}\}$ are real non-negative coefficients corresponding to the (ℓ, k) entries of $N \times N$ combination matrices $\{A_1, A_2\}$. The advantage of using such method is that different choices of $\{A_1, A_2\}$ lead to alternative types. If we choose $A_1 = I_N$ and $A_2 = A$, diffusion ATC is set up. To reach diffusion CTA, we just ought to choose $A_1 = A$ and $A_2 = I_N$, and selecting $A_1 = I_N$ and $A_2 = I_N$ negates the cooperation.

Error signals in diffusion mode are defined in non-stationery conditions as follows:

$$\tilde{\phi}_{k,i} \triangleq \mathbf{w}_i^\circ - \phi_{k,i} \quad (7a)$$

$$\tilde{\psi}_{k,i} \triangleq \mathbf{w}_i^\circ - \psi_{k,i} \quad (7b)$$

$$\tilde{\mathbf{w}}_{k,i} \triangleq \mathbf{w}_i^\circ - \mathbf{w}_{k,i} \quad (7c)$$

The performance analysis method for diffusion algorithms is based on network matrices, in which the same quantities of

the network are collected in a single matrix. Error matrices are then defined as:

$$\tilde{\boldsymbol{\psi}}_i = \begin{bmatrix} \tilde{\psi}_{1,i} \\ \tilde{\psi}_{2,i} \\ \vdots \\ \tilde{\psi}_{N,i} \end{bmatrix}, \quad \tilde{\boldsymbol{\phi}}_i = \begin{bmatrix} \tilde{\phi}_{1,i} \\ \tilde{\phi}_{2,i} \\ \vdots \\ \tilde{\phi}_{N,i} \end{bmatrix}, \quad \tilde{\mathbf{w}}_i = \begin{bmatrix} \tilde{\mathbf{w}}_{1,i} \\ \tilde{\mathbf{w}}_{2,i} \\ \vdots \\ \tilde{\mathbf{w}}_{N,i} \end{bmatrix} \quad (8)$$

Considering the following matrices:

$$\mathcal{M} = \text{diag}\{\mu_1 I_M, \mu_2 I_M, \dots, \mu_N I_M\} \quad (9)$$

$$\mathcal{R}_i = \text{diag}\{\mathbf{u}_{1,i}^* \mathbf{u}_{1,i}, \mathbf{u}_{2,i}^* \mathbf{u}_{2,i}, \dots, \mathbf{u}_{N,i}^* \mathbf{u}_{N,i}\} \quad (10)$$

$$\mathbf{s}_i = \text{col}\{\mathbf{u}_{1,i}^* \mathbf{v}_1(i), \mathbf{u}_{2,i}^* \mathbf{v}_2(i), \dots, \mathbf{u}_{N,i}^* \mathbf{v}_N(i)\} \quad (11)$$

wherein $\text{col}\{\cdot\}$ is used to construct a block column vector, a compact relation is extracted for evolution of error matrix as follows [11]:

$$\tilde{\mathbf{w}}_i = \mathcal{B}_i \tilde{\mathbf{w}}_{i-1} - \mathcal{G} \mathbf{s}_i, \quad i \geq 0 \quad (12)$$

in which:

$$\mathcal{B}_i = \mathcal{A}_2^T (I_{NM} - \mathcal{M} \mathcal{R}_i) \mathcal{A}_1^T \quad (13)$$

$$\mathcal{G} = \mathcal{A}_2^T \mathcal{M} \quad (14)$$

Taking expectation from both sides of (12) we will have:

$$\mathbb{E} \tilde{\mathbf{w}}_i = \mathcal{B}_i \mathbb{E} \tilde{\mathbf{w}}_{i-1} \quad (15)$$

Since the network matrices are used to explain the diffusion mode, the random walk model should also be written in matrix form. For this aim, $\boldsymbol{\zeta}_i$ is defined as follows [7]:

$$\begin{aligned} \boldsymbol{\zeta}_i &= \text{col}\{\boldsymbol{\eta}_i, \dots, \boldsymbol{\eta}_i\} = \mathbb{1}_N \otimes \boldsymbol{\eta}_i \quad (NM \times 1) \\ \mathbb{1}_N &= \text{col}\{1, 1, \dots, 1\} \quad (N \times 1) \end{aligned} \quad (16)$$

Rewriting the mean evolution of diffusion algorithms in non-stationary conditions we have:

$$\mathbb{E} \tilde{\mathbf{w}}_i = \mathcal{B}_i \mathbb{E} \{\tilde{\mathbf{w}}_{i-1} + \boldsymbol{\zeta}_i\} \quad (17)$$

hence, assumed time-varying parameter does not affect the mean behaviour of diffusion algorithms.

Variance relation for diffusion-based networks is formulated in stationary conditions as follows [11]:

$$\mathbb{E} \|\tilde{\mathbf{w}}_i\|_\sigma^2 = \mathbb{E} \|\tilde{\mathbf{w}}_{i-1}\|_{F_{\text{dif}} \sigma}^2 + [\text{vec}(\mathcal{Y}^T)]^T \sigma \quad (18)$$

where:

$$\begin{aligned} F_{\text{dif}} &\approx \mathcal{B}^T \otimes \mathcal{B}^* \\ \mathcal{Y} &= \mathcal{G} \mathcal{S} \mathcal{G}^T \\ \mathcal{S} &= \mathbb{E}\{\mathbf{s}_i \mathbf{s}_i^*\} \end{aligned} \quad (19)$$

This relation is defined for a non-negative $NM \times NM$ matrix Σ and σ is a $N^2 M^2 \times 1$ vector which is extracted from Σ by:

$$\sigma = \text{vec}(\Sigma) \quad (20)$$

The $\text{vec}(\cdot)$ operator vectorizes matrices by stacking its columns on top of each other and also devectorizes column vectors conversely. For compactness, $\text{vec}(\cdot)$ operator is dropped from

(18) in weighting matrices. It can be written in the following form:

$$\mathbb{E}\|\tilde{\mathbf{w}}_i\|_{\Sigma}^2 = \mathbb{E}\|\tilde{\mathbf{w}}_{i-1}\|_{\Sigma'}^2 + [\text{vec}(\mathcal{Y}^T)]^T \sigma \quad (21)$$

wherein:

$$\Sigma' = F_{\text{dif}}\Sigma \quad (22)$$

The variance relation in non-stationary conditions is drawn as follows:

$$\mathbb{E}\|\tilde{\mathbf{w}}_i\|_{\Sigma}^2 = \mathbb{E}\|\tilde{\mathbf{w}}_{i-1}\|_{\Sigma'}^2 + \mathbb{E}\|\zeta_i\|_{\Sigma'}^2 + [\text{vec}(\mathcal{Y}^T)]^T \sigma \quad (23)$$

$\mathbb{E}\|\zeta_i\|_{\Sigma'}^2$ is computed in the following procedure:

$$\begin{aligned} \mathbb{E}\|\zeta_i\|_{\Sigma'}^2 &= \mathbb{E}\text{Tr}(\zeta_i^* \Sigma' \zeta_i) \\ &= \mathbb{E}\text{Tr}(\zeta_i \zeta_i^* \Sigma') \end{aligned}$$

we know that:

$$\begin{aligned} \Sigma' &= \mathbb{E}\mathcal{B}_i^* \Sigma \mathcal{B}_i \\ &= \mathcal{A}_1 \mathcal{A}_2 \Sigma \mathcal{A}_2^T \mathcal{A}_1^T + O(\mathcal{M}) + O(\mathcal{M}^2) \end{aligned} \quad (24)$$

if we neglect $O(\mathcal{M})$ and $O(\mathcal{M}^2)$ for a relatively small step size, we will have:

$$\begin{aligned} \mathbb{E}\|\zeta_i\|_{\Sigma'}^2 &= \mathbb{E}\text{Tr}(\zeta_i \zeta_i^* \Sigma') \\ &= \text{Tr}(\mathbb{E}\zeta_i \zeta_i^* \mathcal{A}_1 \mathcal{A}_2 \Sigma \mathcal{A}_2^T \mathcal{A}_1^T) \\ &= \text{Tr}(\mathcal{R}_{\zeta} \mathcal{A}_1 \mathcal{A}_2 \Sigma \mathcal{A}_2^T \mathcal{A}_1^T) \\ &= \text{Tr}(\mathcal{A}_2^T \mathcal{A}_1^T \mathcal{R}_{\zeta} \mathcal{A}_1 \mathcal{A}_2 \Sigma) \end{aligned} \quad (25)$$

considering:

$$\mathcal{R}_{\zeta} = \mathbb{E}\zeta_i \zeta_i^* = (\mathbf{1}_N \mathbf{1}_N^T) \otimes R_{\eta} \quad (26)$$

The argument in (25) is extended as follows:

$$\begin{aligned} \mathcal{A}_2^T \mathcal{A}_1^T \mathcal{R}_{\zeta} \mathcal{A}_1 \mathcal{A}_2 &= (\mathcal{A}_2^T \otimes I_M (\mathcal{A}_1^T \otimes I_M)) ((\mathbf{1}_N \mathbf{1}_N^T) \otimes R_{\eta}) \\ &\quad \times (\mathcal{A}_1 \otimes I_M) (\mathcal{A}_2 \otimes I_M) \end{aligned} \quad (27)$$

To simplify the obtained relation we note the following lemma:

Lemma 4.1: For arbitrary matrices A_1, A_2, \dots, A_k and B_1, B_2, \dots, B_k the following equality is true:

$$\begin{aligned} (A_1 \otimes B_1)(A_2 \otimes B_2) \dots (A_k \otimes B_k) \\ = (A_1 A_2 \dots A_k) \otimes (B_1 B_2 \dots B_k) \end{aligned}$$

Due to Lemma 4.1 we can write:

$$\begin{aligned} \mathcal{A}_2^T \mathcal{A}_1^T \mathcal{R}_{\zeta} \mathcal{A}_1 \mathcal{A}_2 &= (\mathcal{A}_2^T \mathcal{A}_1^T (\mathbf{1}_N \mathbf{1}_N^T) \mathcal{A}_1 \mathcal{A}_2) \otimes (I_M I_M R_{\eta} I_M I_M) \\ &= (\mathcal{A}_2^T \mathcal{A}_1^T \mathbf{1}_N \mathbf{1}_N^T \mathcal{A}_1 \mathcal{A}_2) \otimes R_{\eta} \\ &= (\mathbf{1}_N \mathbf{1}_N^T) \otimes R_{\eta} \\ &= \mathcal{R}_{\zeta} \end{aligned}$$

Using the following equality for arbitrary matrices W, Σ of compatible dimensions in which $\sigma = \text{vec}(\Sigma)$:

$$\text{Tr}(W\Sigma) = [\text{vec}(W^T)]^T \sigma$$

we have:

$$\text{Tr}(\mathcal{R}_{\zeta} \Sigma) = [\text{vec}(R_{\zeta}^T)]^T \sigma \quad (28)$$

Therefore, (21) is modified in non-stationary mode as follows:

$$\mathbb{E}\|\tilde{\mathbf{w}}_i\|_{\Sigma}^2 = \mathbb{E}\|\tilde{\mathbf{w}}_{i-1}\|_{\Sigma'}^2 + [\text{vec}(\mathcal{Y}^T + \mathcal{R}_{\zeta}^T)]^T \sigma \quad (29)$$

The above relation in vector form is formulated in the following equation:

$$\mathbb{E}\|\tilde{\mathbf{w}}_i\|_{\sigma}^2 = \mathbb{E}\|\tilde{\mathbf{w}}_{i-1}\|_{F_{\text{dif}}\sigma}^2 + [\text{vec}(\mathcal{Y}^T + \mathcal{R}_{\zeta}^T)]^T \sigma \quad (30)$$

Similar to what is proposed in [10] for the stationary mode, the following block diagonal matrices are defined:

$$\begin{aligned} \mathcal{J}_k &= \text{diag}\{0_M, \dots, 0_M, I_M, 0_M, \dots, 0_M\} \\ \mathcal{T}_k &= \text{diag}\{0_M, \dots, 0_M, R_{u,k}, 0_M, \dots, 0_M\} \end{aligned} \quad (31)$$

Hence, the steady-state MSD and EMSE are formulated at each node under non-stationary conditions as follows:

$$\text{MSD}_k = [\text{vec}(\mathcal{Y}^T + \mathcal{R}_{\zeta}^T)]^T \cdot (I - F_{\text{dif}})^{-1} \cdot \text{vec}(\mathcal{J}_k) \quad (32)$$

$$\text{EMSE}_k = [\text{vec}(\mathcal{Y}^T + \mathcal{R}_{\zeta}^T)]^T \cdot (I - F_{\text{dif}})^{-1} \cdot \text{vec}(\mathcal{T}_k) \quad (33)$$

In TVAR model identification problem, the following assumptions are considered:

Assumption 4.2 (TVAR problem):

- 1) All of the distributed nodes are observing the same process: $R_{u,k} = R_u$
- 2) The TVAR model is driven by a white noise. Hence, the process is driven from a circularly Gaussian distribution and the following eigendecomposition is valid: $R_u = U\Lambda U^*$
- 3) The learning rate, μ is assumed to be constant in all nodes: $\mu_k = \mu$

It is proven that in stationary conditions, the following inequality is valid [11]:

$$\text{MSD}_{\text{nep}}^{\text{AR}} \geq \text{MSD}_{\text{cta}}^{\text{AR}} \geq \text{MSD}_{\text{atc}}^{\text{AR}}$$

To discriminate stationary (AR) and non-stationary (TVAR) cases, we use superscripts. If we extend this inequality based on series representation for network MSD [11], we will get:

$$\begin{aligned} \frac{1}{N} \sum_{j=0}^{\infty} \text{Tr}(\mathcal{B}_{\text{nep}}^j \mathcal{Y} \mathcal{B}_{\text{nep}}^{*j}) &\geq \frac{1}{N} \sum_{j=0}^{\infty} \text{Tr}(\mathcal{B}_{\text{cta}}^j \mathcal{Y} \mathcal{B}_{\text{cta}}^{*j}) \\ &\geq \frac{1}{N} \sum_{j=0}^{\infty} \text{Tr}(\mathcal{B}_{\text{atc}}^j \mathcal{Y} \mathcal{B}_{\text{atc}}^{*j}) \end{aligned} \quad (34)$$

If the differences in non-stationary conditions are considered, (34) needs to be modified as follows:

$$\begin{aligned} \frac{1}{N} \sum_{j=0}^{\infty} \text{Tr}(\mathcal{B}_{\text{nep}}^j (\mathcal{Y} + \mathcal{R}_{\zeta}) \mathcal{B}_{\text{nep}}^{*j}) &\geq \frac{1}{N} \sum_{j=0}^{\infty} \text{Tr}(\mathcal{B}_{\text{cta}}^j (\mathcal{Y} + \mathcal{R}_{\zeta}) \mathcal{B}_{\text{cta}}^{*j}) \\ &\geq \frac{1}{N} \sum_{j=0}^{\infty} \text{Tr}(\mathcal{B}_{\text{atc}}^j (\mathcal{Y} + \mathcal{R}_{\zeta}) \mathcal{B}_{\text{atc}}^{*j}) \end{aligned} \quad (35)$$

Lemma 4.2: For arbitrary matrices A, B, and C and a non-negative matrix Σ

$$\text{Tr}(ABC) \leq \text{Tr}(A(B + \Sigma)C)$$

As it can be seen in lemma (4.2), the terms are increased monotonically. Since the increase is constant throughout the inequality, it will not change. Therefore, we can write for TVAR problem:

$$\text{MSD}_{\text{nep}}^{\text{TVAR}} \geq \text{MSD}_{\text{cta}}^{\text{TVAR}} \geq \text{MSD}_{\text{atc}}^{\text{TVAR}} \quad (36)$$

V. EXPERIMENTAL RESULTS

The real data set being discussed in this paper was collected at the third SensIT situational experiment (SITEX02), organized by DARPA/IXOs SensIT (Sensor Information Technology) program available at [12]. In this real raw dataset, 23 WINS NG 2.0 [13] nodes were dispersed over a geographical region. During the experiment, two vehicles went through this region and the nodes recorded three modalities: acoustic, seismic and infra red. In this paper, we focus on the acoustic modality.

We consider that the spatio-temporal signal source produces a complex circular Gaussian field in the spatial and temporal dimensions. Since the field is generated by a moving signal source, a fixed sensor observes an approximately Gaussian process. This assumption helps us to establish the spatial coherence regions [14].

The quality of the estimation in a collaborative routine is closely related to the quality and validity of the shared data. In this experiment, sensor nodes are distributed over a considerably large area. Considering that the moving signal source will be near a particular set of nodes at each time instant, obviously collaborating among all nodes is not effective at all. To solve this challenge, some coherent cells should be considered, wherein the observations are correlated. Based on the proposed approximation in [14], [15], rectangular cells are chosen with the following slides:

$$D_{c,x} = \frac{v}{B_t} \quad (37)$$

in which v is the sound speed and B_t is the bandwidth of the underlying temporal signal. Considering $B_t = 50\text{Hz}$, we divide the entire field into some rectangular cells as indicated in Fig.1.

To select an appropriate order for the underlying TVAR model, minimum description length (MDL) criterion is used [16],

$$\text{MDL}(M) = l \ln(\sigma_v') + M \ln(l) \quad (38)$$

in which, M and l denote order and length, respectively. In this criterion, σ_v' is the estimated additive noise variance. The desired order (M) is then obtained by minimizing MDL. To use this AR-oriented criterion, we applied the MDL to 250 ms sections of a sample recorded signal and extracted the best order for each section. Afterwards, the maximum section order is considered as the best. Using this strategy, we employ $M = 10$.

The other challenge in this implementation is that the desired vector is unknown. To calculate MSD and EMSE in each algorithm, we need to have a known desired vector. For that, we assumed a centralized adaptive algorithm [17], in which

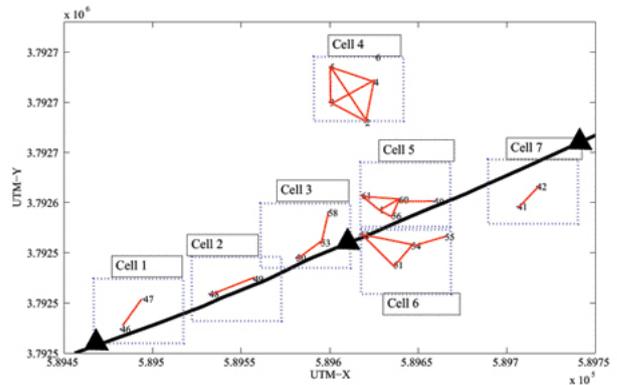


Fig. 1. AAV3 Trajectory.

the estimation is calculated based on all nodes' observations, prepares a great deal more accurate parameter compared to diffusion networks. As a result, the estimated parameter obtained by a centralized adaptive scheme considered to be the desired parameter, and other algorithms are compared to it.

We ran different algorithms to estimate the acoustic signature of the moving vehicle for the test named AAV3. The trajectory is depicted in Fig. 1, as well as the considered diffusion topology in each cell.

Network MSD and EMSE for different cells are depicted in Figs. 2 and 3. Based on the trajectory shown on Fig.1, we expect that the first distortion occurs in cell 7, and the last in cell 1, respectively. Since, the moving source has not passed cell 4, we do not expect any distortion there. These expectations are well observable in both MSD and EMSE plots. The obtained order for MSD in (36) is valid through all cells. A considerable difference occurs in cells 1, 2, 4 and 7, where we have fully-connected diffusion networks. All nodes in a fully-connected diffusion ATC network act as a fusion center, hence the network resembles the centralized algorithm's performance. Yet, the expected order is not broken.

The network EMSE in different cells is depicted in Fig. 3. EMSE shows the ability of the estimated parameter to construct the signal. While, EMSE experiences oscillation due to the high obtained accuracy, the obtained order for MSD is still valid.

VI. CONCLUSION

In this paper, we employed diffusion adaptive networks for acoustic signature estimation. Considering TVAR model for acoustic signature we proposed employing diffusion adaptive networks for model identification problem. To analyze the performance of the proposed algorithms, we thoroughly considered and extracted the network MSD and EMSE under non-stationary conditions. Afterwards, based on the obtained error criteria and under TVAR modeling problem conditions, diffusion ATC and CTA were compared with a non-cooperative algorithm. The comparison proved the superiority of diffusion ATC and CTA, respectively. Using the proposed methods we

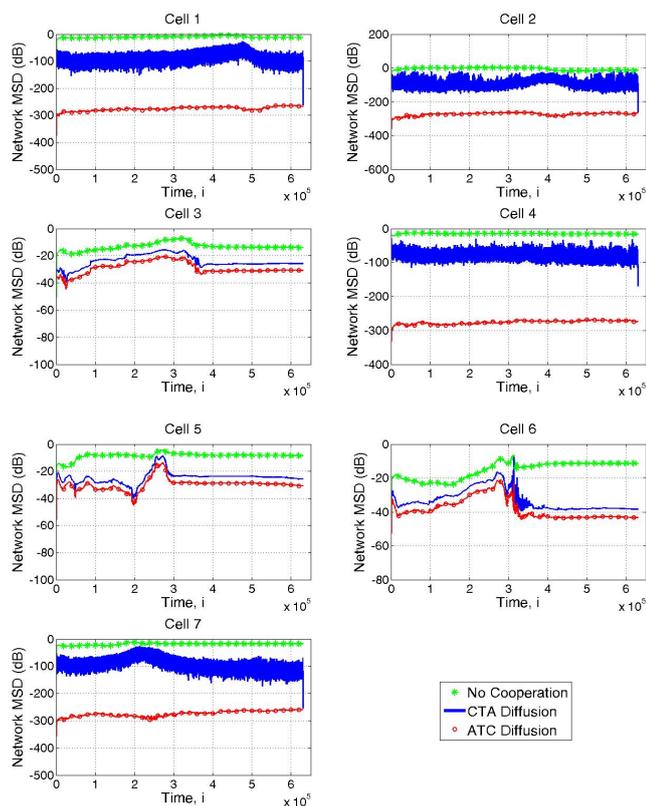


Fig. 2. Network MSD in each cell.

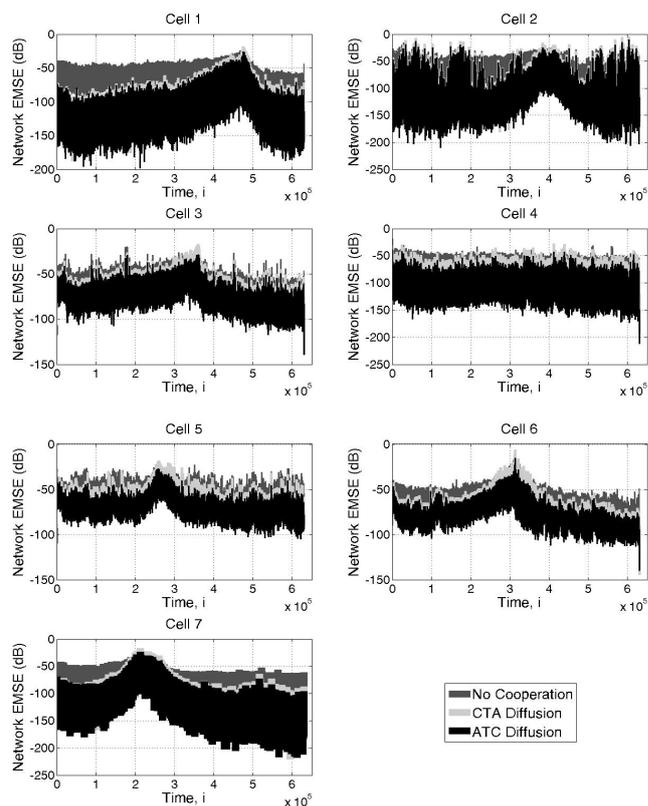


Fig. 3. Network EMSE in each cell.

implemented diffusion adaptive networks on an experimental real raw data for the first time, and the practical error criteria were calculated. The experimental results supported the theoretical achievements and approved effectiveness of the proposed framework.

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