On the Region of Feasibility of Interference Alignment in Underwater Sensor Networks

Parul Pandey, *Student Member, IEEE,* and Dario Pompili, *Member, IEEE*

***Abstract*—To enable underwater applications such as coastal and tactical surveillance, undersea explorations, and picture/video acquisition, there is a need to achieve high data-rate underwater acoustic communications, which translates into attaining high acoustic channel spectral efficiencies. Interference Alignment (IA) technique, which has recently been proposed for radio-frequency MIMO terrestrial communication systems, aims at improving the spectral efficiency by enabling nodes to transmit data simultaneously at a rate equal to half of the interference-free channel capacity. While promising, there are challenges to be solved for the use of IA underwater, i.e., imperfect acoustic channel knowledge, high computational complexity, and high communication delay. In this paper, a feasibility study on the practical employment of IA underwater is presented, and a novel distributed computing framework for sharing processing resources in the network so to parallelize an iterative IA algorithm is proposed.**

***Index Terms*—Underwater acoustic networks, MIMO technology, interference alignment, channel estimation.**

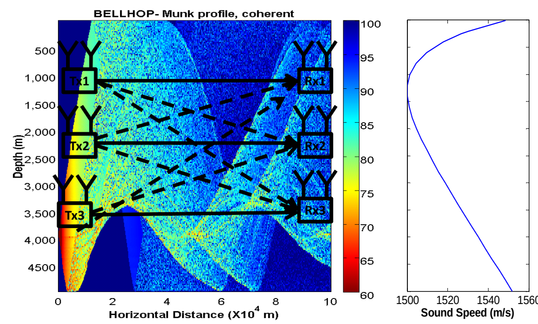


Fig. 1. An UW-ASN with $K = 3$ users (i.e., 3 Tx-Rx pairs) with $N_T = N_R = 2$ (two antennae on each node). For a clear visualization, we have shown the Bell-hop channel profile associated only with Tx_3. The transmission loss of the channel is given in dB. Here, we used the Munk sound speed profile (right subfigure) with the depth being the same as in the left subfigure.

I. Introduction

UnderWater Acoustic Sensor Networks (UW-ASNs) [1] consist of static and mobile sensors deployed to perform collaborative monitoring tasks over a body of water. These networks enable oceanographic applications such as environmental monitoring, offshore exploration, and video-assisted navigation. Due to propagation limitations of Radio Frequency (RF) and optical signals, i.e., high medium absorption and scattering, respectively, acoustic communication technology is employed for transfer of information between underwater sensors. However, because of the limited acoustic bandwidth available, there is a need to maximize the underwater network capacity. This is essential in order to enable high data-rate multimedia applications such as video/audio stream transfer, transfer of metadata associated with these streams, and time-critical monitoring processes.

In terrestrial systems, Multiple Input Multiple Output (MIMO) systems have been proposed to enable high data-rate applications. These systems are able to exploit the scattering and multipath fading in such a way as to provide higher spectral efficiencies using the same transmission output power. MIMO technology can in fact take advantage of the rich scattering and heavy multipath of the underwater acoustic environment so to increase data transmission rates and improve link reliability in UW-ASNs [2], [3]. While still not mature, the promise of this technology has also being recognized by the underwater acoustic communication community in recent years.

In order to increase the spectral efficiency of multi-user wireless terrestrial networks, a technique called Interference Alignment (IA) has been proposed [4], [5]. This technique enables the transmitter-receiver pairs ("users") to transmit data simultaneously at a rate equal to half of their interference-free channel capacity. The goal of IA is to design transmit signals for all users in such a way that the interfering signals at each receiver fall in the subspace that is linearly independent of the subspace of the desired signal. The receiver then applies an interference suppression filter to project the desired signal onto the interference-free dimension of the network. This is a very promising technique to enable high data-rate applications by increasing the spectral efficiency of the channel. To the best of our knowledge, this is first time IA technique is being proposed to improve underwater acoustic communications.

There are a few research challenges that need to be solved for the practical use of IA underwater, namely, *imperfect channel knowledge*, *high computational complexity*, and *high communication delay*. Existing IA algorithms assume perfect knowledge of the channel at the communicating nodes; however, the accurate estimation of the time- and space-varying underwater acoustic channel is a challenging task itself. The propagation speed of acoustic waves varies with water temperature, salinity, and pressure (i.e., depth), which causes wave paths to bend towards regions of lower sound speed (as shown in Fig. 1). Acoustic waves are also reflected

The authors are with the Department of Electrical and Computer Engineering, Rutgers University, New Brunswick, NJ. Their emails are parul, pompili@cac.rutgers.edu. This work was supported by the NSF CAREER Award No. OCI-1054234.

from the surface and bottom. Such uneven propagation of waves results in *convergence (or shadow) zones*, which are characterized by lower (or higher) transmission loss.

In this paper, we study the effect of inaccurate estimation of underwater acoustic channel on the technique of IA. We also study the tradeoffs of multiplexing and link reliability, power, and number of concurrent users associated with IA. Also, to overcome the challenge of computational complexity and communication delay, we introduce a novel distributed computing framework for sharing processing resources in the network. We provide the computing infrastructure to support the distributed capabilities of existing IA algorithms by forming an *elastic resource pool*; using the collective computational capability of this pool of neighboring nodes, parallel tasks can be performed. We present a study on the potential increase in the *region of feasibility* of compute-intensive IA techniques in UW environment through our framework. This involves studying the trade-off between computational gain (in terms of speed up over stand-alone computation) versus communication (and delay) overhead incurred as well as its effect on the performance in terms of spectral efficiency for data transmission. This tradeoff helps us define the scenarios in which the distributed realization of IA technique is feasible in UW environment.

The following are the main contributions of this paper.

- We study whether it is feasible and practical to use IA underwater under different channel and network conditions. We also study the tradeoff between multiplexing and link reliability, power, and number of concurrent users associated with IA;
- We propose a distributed framework to parallelize the iterative IA algorithm in underwater environment and show the gains via simulations in terms of increase in network capacity.

The rest of the paper is organized as follows: in Sect. II, we provide the necessary background on IA and study the various tradeoffs associated with this technique; in Sect. III, we propose a distributed grid computing framework and explain how we exploit it to realize distributed IA; in Sect. IV, we evaluate the performance of our proposed approach; finally, in Sect. V, we draw the conclusions and provide a brief note on future work.

II. BACKGROUND

In this section, firstly we present a brief background on IA and study the effect of imperfect channel conditions on the performance of IA. Secondly, we discuss the tradeoff between multiplexing and link reliability in IA. We also study the need for power control, which is aimed at selecting an optimal transmission power so to avoid impairing the ongoing communications of neighboring nodes while at the same time guaranteeing minimum power requirement for a transmission to occur successfully. Finally, we discuss the computational complexity of distributed IA algorithms.

Interference Alignment: We consider a generic system model, a K-user interference channel system as shown in Fig. 1. Each transmitter Tx is equipped with N_T antennas,

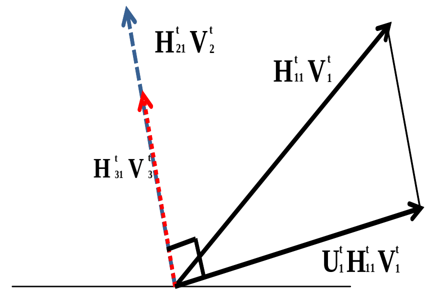


Fig. 2. Under *perfect channel knowledge*, interfering signals $\mathbf{H^t_{21}V^{t_2}}$ and $\mathbf{H_{31}}^t\mathbf{V}^t_3$ align perfectly.

and each receiver Rx is equipped with N_R antennas. Each Tx_i is communicating with Rx_i $\forall i = 1 \dots K$ [6], [7]. When $K = 2$ and $N_T = N_R = 2$, the channel between transmitter i and receiver j is given as $\mathbf{H_{ij}}$, which can be decomposed as

$$\mathbf{H_{ij}} = \begin{bmatrix} h^{ij}_{11} & h^{ij}_{12} \\ h^{ij}_{21} & h^{ij}_{22} \end{bmatrix}, \tag{1}$$

where each entry h^{ij}_{kl} is a complex number whose magnitude represents the signal attenuation from transmitter antenna k to receiver antenna l in a time slot and whose phase represents the propagation delay (in Fig. 1, $k, l \in \{1, 2\}$). At transmitter i, $\mathbf{x_i}$ is a $d_i \times 1$ symbol vector where d_i is the number of independent information streams or the degree of freedom for the i^{th} transmitter. The goal of IA is to design transmit precoding matrices $\mathbf{V_i}$ of dimensions $N_T \times d_i$ for each transmitter. The transmitted signal is then given as $\mathbf{s_i} = \mathbf{V_i x_i}$ of dimension $N_T \times 1$. These matrices are chosen such that by encoding with them all the interfering signals lie in a subspace that is linearly independent of the subspace of the desired signal. The heart of IA in spatial domain lies in constructing these transmit precoding vectors. To decode, the receiver projects the received signal onto a vector that is orthogonal to the vector of interfering signal. The received signal vector at receiver j is given as,

$$\mathbf{r_i} = \mathbf{H_{ii}V_i x_i} + \sum_{j=1, i\neq j}^{K} \mathbf{H_{ji}V_j x_j} + \mathbf{n_i}, \tag{2}$$

where the first term is the desired signal at Rx_i and the second term is the interference from all other transmitters. Here, $\mathbf{n_i}$ is the $N_R \times 1$ Additive White Gaussian Noise (AWGN) or thermal noise vector.

Interference Cancelation To decode, the receiver projects the received signal onto a *decoding vector*, $\mathbf{U_i}$, that is orthogonal to the data vector of interfering signal. Such decoding vector can be found by imposing $\mathbf{U_i} = null(\mathbf{H_{ji}V_i}) = null([\mathbf{H_{ki}V_k}]^\dagger)$, where † represents the Hermitian or conjugate transpose and *null* represents the null space of a generic matrix $\mathbf{A}$, i.e., the set of all vectors $\mathbf{x}$ for which $\mathbf{Ax}$ = 0. After applying the interference suppression filter, i.e., $\mathbf{U_i}^\dagger$,

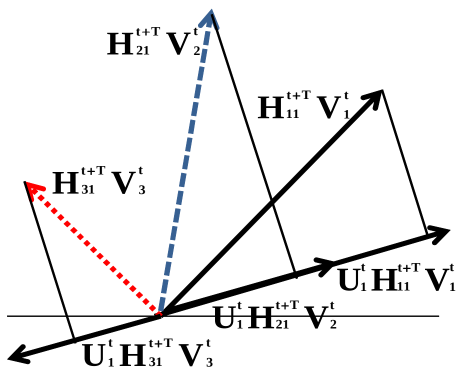


Fig. 3. Under *imperfect channel knowledge*, interfering signals $\mathbf{H_{21}}^{t+T}\mathbf{V}_2^t$ and $\mathbf{H_{31}}^{t+T}\mathbf{V}_3^t$ do not align, thus resulting in residual interference (leakage).

the received signal at receiver i is given as,

$$\mathbf{y_i} = \mathbf{U_i}^{\dagger}\mathbf{H_{ii}}\mathbf{V_i}\mathbf{x_i} + \sum_{j=1, j\neq i}^{K} \mathbf{U_i}^{\dagger}\mathbf{H_{ji}}\mathbf{V_j}\mathbf{x_j} + \mathbf{U_i}^{\dagger}\mathbf{n_i}. \quad (3)$$

The second term in (3) is the total interference at receiver i, which is called *interference leakage*. The interference leakage at Rx_i is defined as, $\sum_{j=1,j\neq i}^{K} ||\mathbf{U_i}\mathbf{H_{ji}}\mathbf{V_j}||$. In case of ideal IA, i.e., when the channel knowledge is perfect, the interference signals lie in the same subspace and the interference suppression filter eliminates the interference completely.

Channel information and interference leakage: We now discuss about the effect of perfect and imperfect channel knowledge at the communicating nodes on the IA technique.

Perfect channel knowledge: Let us consider a $K = 3$ user system with $N_T = N_R = 2$ and $d_i = 1$, where d_i is the number of independent streams transmitted by Tx_i. The channel from TX_i to RX_i at time t is given as $\mathbf{H_{ii}}^t$. According to IA, in the case of perfect channel knowledge the interfering signals lie in the same subspace that is independent of the subspace of the desired signal. Fig. 2 shows the signals received at Rx_1. Signals $\mathbf{H_{21}}^t\mathbf{V_2}^t$ and $\mathbf{H_{31}}^t\mathbf{V_3}^t$ are interference signals and $\mathbf{H_{11}}^t\mathbf{V_1}^t$ is the desired signal. The dimension of the received signals is $2 \times d_i$ (i.e., $N_T \times 1$ in this example). We see that both the interference signals align, i.e., overlap, perfectly. The interference suppression filter is then applied to these interference signals, which completely cancels these signals. In case of ideal interference alignment, the decoding vector $\mathbf{U_1} = null(\mathbf{H_{21}}\mathbf{V_2}) = null([\mathbf{H_{31}}\mathbf{V_3}]^{\dagger})$, i.e, it lies in the null space of the interference signals. Hence, in the case of perfect channel knowledge we have,

$$\mathbf{U_i}^t\mathbf{H_{ji}}^t\mathbf{V_j}^t = \mathbf{0}, \forall j \neq i, \quad (4)$$

i.e., the interference leakage is completely removed by the interference suppression filter and

$$rank(\mathbf{U_i}^t\mathbf{H_{ii}}^t\mathbf{V_i}^t) = d_i \quad (5)$$

represents the rank of the desired signal, i.e., the number of parallel streams (also known as *degree of freedom*).

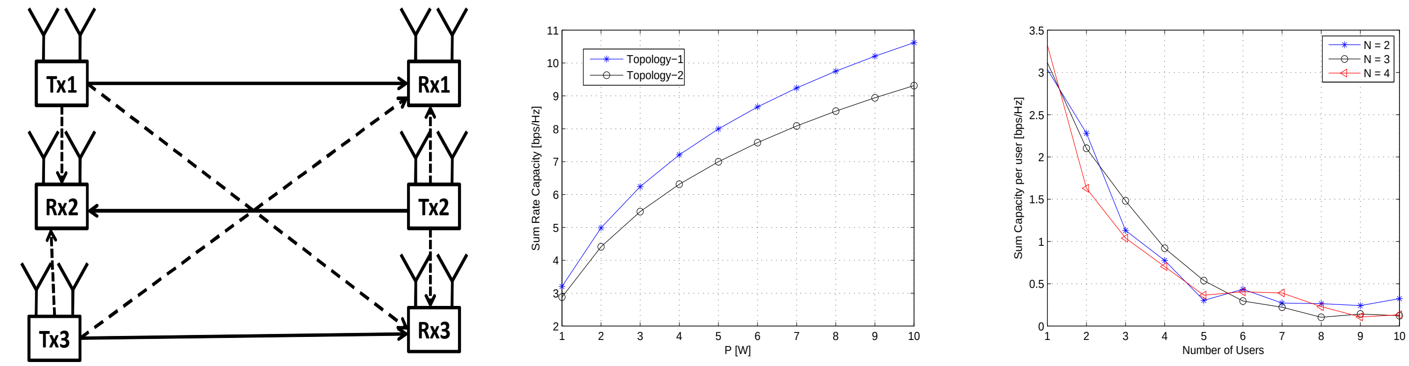
Imperfect channel knowledge: Now we consider the alignment at Rx_1 after T [s] from the last channel probing at instant t. We assume that the channel has changed with time and the new updated channel matrix is $\mathbf{H}^{t+T}$. We also assume that the nodes do not have updated channel information. As a result, they continue to use the precoding and decoding vectors estimated at time t (i.e., $\mathbf{V_i}^t$ and $\mathbf{U_i}^t$). Figure 3 shows the interference alignment at Rx_1. The interference signals ($\mathbf{H_{21}}^{t+T}\mathbf{V_2}^t$ and $\mathbf{H_{31}}^{t+T}\mathbf{V_3}^t$) no longer align perfectly as in the case of Fig. 2. This is because the channel has changed and the precoding/decoding used are estimated based on the old channel knowledge $\mathbf{H}^{t+T}$. Hence, the interfering signals no longer lie in the same subspace. Also, a new interference suppression filter needs to be estimated to cancel the interference. As a result, after applying the interference suppression filter $\mathbf{U}_1^t$ the interference is not completely canceled out. The interference leakage in this case is

$$\mathbf{U_i}^t\mathbf{H_{ji}}^{t+T}\mathbf{V_j}^t \neq \mathbf{0}, \forall j \neq i. \quad (6)$$

As a result, the Bit Error Rate (BER) increases, which leads to the corresponding decrease in *net bit rate*, given by $D^N = d_i \cdot C_{Tx} \cdot (1 - BER)$, where the capacity C_{Tx} is given as a product of the used bandwidth, B [kHz], and the spectral efficiency of the modulation, η [bps/Hz]. The capacity of each individual data stream is multiplied by the number of parallel streams of the network to obtain the overall capacity of the MIMO system. The higher d_i (i.e., the higher the degree of multiplexing), the higher the spectral efficiency of the MIMO system. We will now discuss the tradeoffs associated with IA and how they affect its performance.

Multiplexing and link reliability: In MIMO transmissions, to increase the spectral efficiency multiple data streams are sent out in parallel. The increase in spectral efficiency by transmission of multiple independent parallel streams in comparison to a single stream is called *multiplexing gain*. If d_i is the number of independent streams sent out, then the multiplexing gain is d_i. The transmitted signal $\mathbf{V_i}\mathbf{x_i}$ at TX_i is of dimension $N \times d_i$. At Rx_i, the rank of the subspace of the desired signal is d_i. For perfect alignment, according to the theory of IA, the subspace of interfering signals $\mathbf{V_j}\mathbf{x_j}$ should have a rank $N - d_i$ and should span the same subspace, linearly independent from the desired-signal subspace. In case of imperfect channel estimation, however, the interference signals may no longer occupy the same interference subspace. To overcome this effect, the number of independent streams d_i at the transmitter can/should be reduced. This allows the interference to span across a higher dimension subspace, which leads to low interference leakage and, hence, to a low BER. However, although this low BER gives a high link reliability, it comes at a cost of a lower multiplexing gain, which explains the multiplexing vs. link reliability tradeoff.

Power control: To visualize the effect of transmission power on IA, we consider two types topologies. Topology 1 is similar to that in Fig. 1, where all transmitters and receivers are equidistant from each other; whereas Topology 2 is given in Fig. 4(a). We see that due to the proximity of Tx_1 to Rx_2



(a) (b) (c)

Fig. 4. (a) Topology to visualize the *near-far effect* on the technique of IA; (b) Variation of spectral efficiency with topology; (c) Variation of network capacity with number of users for different number of antennae ($N = 2, 3, 4$).

in Fig. 4(a) the signal received from Tx_1 is stronger than that received from Tx_2. This is an example of the *near-far effect*, which in general occurs when the signal received by a receiver from a sender near the receiver is stronger than the signal received from another sender located further. In this case, the remote sender will be dominated by the close sender. In Fig. 4(a), we can see that the signal from Tx_2 will cause interference at Rx_1. The residual interference at RX_1 will be $\sum_{j=2,j\neq i}^{3} P^j||\mathbf{U_1 H_{j1} V_j}||$. Hence, the higher the power of TX_1, the higher the interference leakage will be. Figure 4(b) compares the spectral efficiency of the system associated with the two extreme topologies. We see that the spectral efficiency of the system for Topology 2 is lower than that for Topology 1. This motivates the need for a *power-control mechanism* that avoids impairing the ongoing communications of neighboring nodes and at the same time is able to guarantee the minimum power requirement for the transmission to occur successfully.

Number of active users: In the case of imperfect channel estimation, the interference leakage $\sum_{j=1,j\neq i}^{K}||\mathbf{U_i H_{ji} V_j}||$ cannot be neglected. Specifically, as the number of users K increases, the interference leakage also increases, leading to higher BER (i.e., lower link reliability). In Fig. 4(c) we see that as K increases the capacity per user of the system decreases; on the other hand, if K is too low, the gain from IA is not exploited properly.

Computational complexity and communication delay: IA algorithms used for estimating the precoding/decoding vectors (e.g.,[8], [9]) are compute intensive as they involve multiple eigen-vector calculations and matrix multiplications. These calculations need to be performed in a fraction of the channel coherence time T_c (defined as the duration over which the impulse response is considered to be time invariant) so that the estimated precoding/decoding vectors are reusable for the remaining time of the coherence time. Also, the existing IA algorithms require exchange of information between transmitter and receiver, which cannot happen instantaneously due to the large underwater communication delay (due to propagation and transmission delays). If T_c is smaller than the time taken to compute the precoding/decoding vectors, then these vectors will not be useful as the channel conditions will have changed. To overcome these issues, we propose a distributed computing framework that reduces the computation time for estimating the precoding vectors by executing in parallel the tasks composing the IA algorithm. Such framework, however, introduces some overhead, which needs to be absorbed by the gain it brings (i.e., reducing the overall execution time of the IA distributed algorithm): this is another tradeoff involving computational complexity and communication delay.

III. Distributed Computing Framework

Existing IA algorithms are computationally intensive and require exchange of information between transmitter and receiver, which cannot happen "instantaneously" (as desirable ideally) due to the large underwater propagation delay. If the coherence time of the channel (T_c) is smaller than the time taken to compute the precoding/decoding vectors, then these vectors will not be useful as the channel conditions will have changed. To overcome this issue, we propose a distributed computing grid framework [10] that reduces the computation time for estimating the precoding vectors by executing in parallel the tasks composing the IA algorithm.

Distributed IA Algorithm: We now present an iterative IA algorithm [8] for which our framework provides computing infrastructure to support its distributed capabilities. This algorithm is computationally intensive as it involves multiple matrix and eigen-vector calculations. The total residual interference at the receiver of user j due to interference from all undesired transmitters ($k \neq j$) is given by,

$$\mathbf{I_j} = Tr[\mathbf{U_j}^\dagger \mathbf{Q_j} \mathbf{U_j}],\ \mathbf{Q_j} = \sum_{k=1,k\neq j}^{K} \frac{\mathbf{P_k}}{d_k} \mathbf{H_{kj}} \mathbf{V_k} \mathbf{V_k}^\dagger \mathbf{H_{kj}}^\dagger, \tag{7}$$

where $\mathbf{P_k}$ is the transmit power at transmitter k. Each of the d_j columns of $\mathbf{U_j}$ are given by, $\mathbf{U_{j[n]}} = \nu_n[\mathbf{Q_j}],\ n = 1, \ldots, d_j$, where $\nu_n[\mathbf{Q_j}]$ is the eigenvector corresponding to the n^{th} smallest eigenvalue of $\mathbf{Q_j}$. In the beginning of the iterative algorithm, the transmit precoding vectors are initialized with some random values and interference suppression filter of the original network are calculated using (7). After determining $\mathbf{U_j}$, the transmitter and receiver switch their roles. This network is called a "reciprocal" network. The estimated

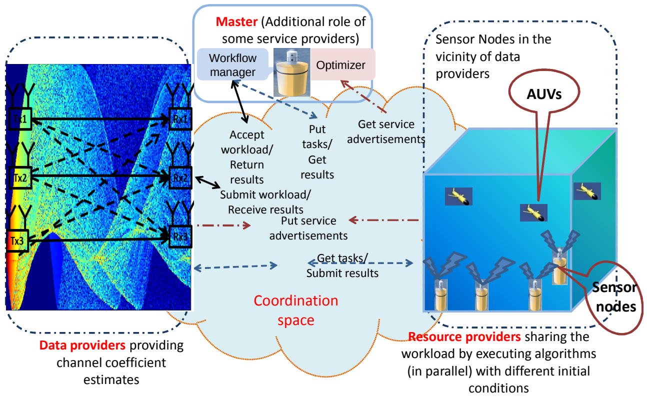


Fig. 5. An overview of the envisioned distributed computing framework for optimizing compute-intensive IA algorithms

interference suppression filter ($\mathbf{U_j}$) of the original network now become the precoding vectors ($\overleftarrow{\mathbf{V_j}}$) for the reciprocal network. The arrow at the top indicates that this vector belongs to the reciprocal network. Similarly to the original network, in the reciprocal network (with transmitters and receivers switched) the total interference leakage at receiver j due to interference from all undesired transmitters ($k \neq j$) is given by, $\overleftarrow{\mathbf{I_j}} = Tr[\overleftarrow{\mathbf{U_j}}^{\dagger}\overleftarrow{\mathbf{Q_j}}\overleftarrow{\mathbf{U_j}}]$. The interference suppression filter ($\overleftarrow{\mathbf{U_j}}$) for the receivers of the reciprocal network are calculated only to be used as the transmit precoding vectors of the original network in the next iteration. The iterative algorithm alternates between the original and reciprocal networks with only the receivers updating their interference suppression filter (in every iteration) to minimize their total leakage interference.

Leveraging the distributed framework in UW-ASNs: In our framework, one of the node serves as the "master," i.e., it is responsible for parallelizing the tasks between transmitter/receiver pair and the nodes in the neighborhood, called Service Providers (SPs). We assume that only the communicating nodes are service providers. Our scenario is shown in Fig. 5. Each communicating node estimates the channel from itself to all other communicating nodes and broadcasts this information. The master chooses *equally spaced initial conditions* for the iterative IA algorithm so to ensure good coverage of the n-dimensional search space and to avoid choosing final precoding/decoding vectors "stuck" in local minima, hence, suboptimal. The master transmits a unique initial condition to each SP and the number of iterations required to execute the iterative algorithm. Once the SPs have computed the precoding vectors, they send their results to the master, which selects the vector pair that maximizes the network spectral efficiency. In this computing grid framework, each node executes the iterative algorithm locally: this way, by incurring only small communication overhead caused by message exchanged among the nodes of the mobile grid, we overcome the challenge of high communication delay.

IV. Performance Evaluation

In this section we study the performance gains achieved through IA in terms of spectral efficiency in UW environment. We consider both the scenarios of perfect and imperfect channel knowledge at the nodes. We also investigate the effectiveness of the proposed framework for IA via simulations. We present a study on the potential increase in the region of feasibility of compute-intensive IA techniques in UW environment using our framework.

We model the UW channel using the Urick model. The Urick model is used to estimate the transmission loss $TL(l,f)$ [dB] as,

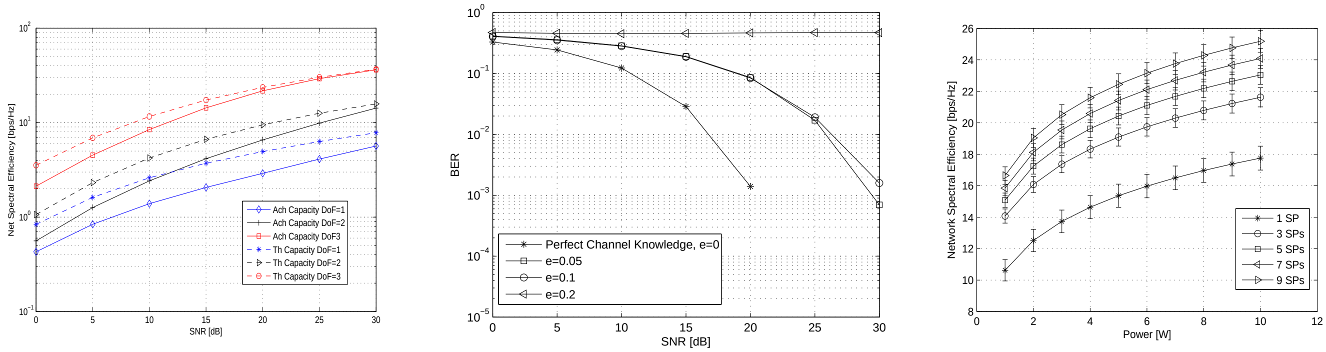
$$TL(l,f) = \kappa 10 log(l) + \alpha(f)l + A, \tag{8}$$

where l [m] is the distance between the transmitter and receiver and f [Hz] is the carrier frequency. Spreading factor κ is taken to be 1.5 for practical spreading, and $\alpha(f)$ [dB/m] represents an absorption coefficient that increases with f. The last term, expressed by the quantity A [dB], is the transmission anomaly. We adopt the empirical ambient acoustic noise model presented in [11], where the "V" structure of the noise power spectrum density (psd) is shown. We consider a deployment region of $1(L) \times 1(W) \times 1(H)$ km^3. The carrier frequency and bandwidth are assumed to be 10 kHz and 20 kHz respectively.

Figure 6(a) depicts the measured and the theoretical spectral efficiency versus Signal to Noise Ratio (SNR) for different degrees of freedom (DoF), a capacity characterization of the network that is accurate within $\mathrm{O}(\log SNR)$. We observe that the measured spectral efficiency does not increase at the same rate as the theoretical one, which can therefore be used as an upper bound. We assume the channel knowledge to be perfect in this case.

We now consider the effects of imperfect channel knowledge, where the error in estimation of channel coefficients can be modeled as $\bar{\mathbf{H}} = \mathbf{H} + \mathbf{e\Omega}$, where $\mathbf{e\Omega}$ is the error (assumed uncorrelated with $\mathbf{H}$). The entries of $\mathbf{\Omega}$ are i.i.d. zero-mean complex Gaussian with unity variance and $\mathbf{e}$ is a parameter modeling how accurate the channel estimation is [12]. Figure 6(b) shows the variation of BER as the SNR varies. We see that the BER increases as $\mathbf{e}$ increases. The value of $\mathbf{e}$ ranges from 0 to 0.2, where 0 indicates perfect channel knowledge. Here, the DoF is assumed to be 1. As the channel error ($\mathbf{e}$) increases from 0 to 0.2, the spectral efficiency decreases by 70%. This indicates that the practical implementation of IA depends largely on the quality of our channel estimates. We now consider the performance gains in terms of spectral efficiency from our distributed framework. In Fig 6(c), we see the network spectral efficiency (sum of spectral efficiency of all the users in the network) versus power; as the number of service providers (SPs) increases, the network spectral efficiency increases. Specifically, as the number of SPs increases from 1 to 3, the spectral efficiency increases by 5 kbps/Hz. For a 20kHz-system, the spectral efficiency increases by 100 kbps. The number of iterations for all service providers is assumed to be 10.

Let us compare the case where the entire iterative algorithm is executed at one node (one SP) with the case where the number of computing nodes, i.e., SPs, is greater than two. From Fig. 7, we see that, for the same topology, as the number of SPs increases, the estimation time (sum of computation time for calculating precoding/decoding vectors and



(a) (b) (c)

Fig. 6. (a): Variation of the theoretical and net spectral efficiency with SNR under perfect channel conditions; (c): BER vs SNR with different degrees of inaccuracy in channel knowledge; (c) Variation of network spectral efficiency with power for different number of SPs.

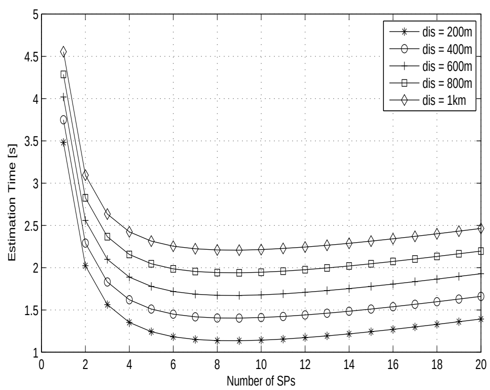


Fig. 7. Variation of minimum estimation time of precoding/decoding matrices with number of SPs. The distance indicates the maximum distance assumed between a transmitter and receiver in the network.

the communication time between master and SPs) decreases. For example, when the number of SPs increase from 1 to 5 for a distance of 800 m, the estimation time reduces from 4.25 to 2 s, i.e, a reduction by more than 50%. Hence, for a given coherence time, a high enough number of SPs allows the use of precoding vectors for a longer duration (thus bringing savings in terms of probing overhead). We can also see that as the number of SPs increases beyond eight, the estimation time starts to increase. This increase in computation time can be attributed to the increase in coordination time between master and SPs. Although the spectral efficiency increases as the number of SPs increases (as shown in Fig. 6(c)), the estimation time also increases. As a result, the estimated precoding/decoding vectors will be useful for a shorter duration of time, which provides a quantitave example of the tradeoff between communication overhead and computational gain.

V. Conclusion and Future Work

We studied the effect of inaccurate channel estimation on the technique of Interference Alignment (IA). We showed via simulations the tradeoffs under different UndeWater (UW) acoustic channels and network topologies. We observed that the performance gain (in terms of spectral efficiency) depends on the quality of the channel estimates. We proposed a distributed computing framework for the UW environment to overcome the challenge of computational complexity and communication delay faced by IA algorithms. We observed that parallelism is not only possible (notwithstanding the large acoustic propagation delays) but in fact increases the region of feasibility. As a future work, we plan to implement our proposed solution on an emulator with real WHOI acoustic modems, with the UW acoustic channel simulated using the Bellhop model.

References

[1] D. Pompili and I. Akyildiz, "A Cross-layer Communication Solution for Multimedia Applications in Underwater Acoustic Sensor Networks," in *Proc. of IEEE International Conference on Mobile Ad-hoc and Sensor Systems (MASS)*, Atlanta, GA, October 2008.

[2] D. Kilfoyle, J. Preisig, and A. Baggeroer, "Spatial Modulation Experiments in the Underwater Acoustic Channel," *IEEE Journal of Oceanic Engineering*, vol. 30, no. 2, pp. 406–415, April 2005.

[3] A. Harris and M. Zorzi, "On the Design of Energy-efficient Routing Protocols in Underwater Networks," in *Proc. of IEEE International Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON)*, San Diego, CA, June 2007.

[4] V. Cadambe and S. Jafar, "Interference Alignment and Degrees of Freedom of the K-user Interference Channel," *IEEE Transactions on Information Theory*, vol. 54, no. 8, pp. 3425–3441, August 2008.

[5] A. Ghasemi, A. Motahari, and A. Khandani, "Interference Alignment for the K-user MIMO Interference Channel," in *Proc. of IEEE International Symposium Information Theory Proceedings (ISIT)*, Austin, TX, June 2010.

[6] S. Jafar and M. Fakhereddin, "Degrees of Freedom for the MIMO Interference Channel," *IEEE Transactions on Information Theory*, vol. 53, no. 7, pp. 2637–2642, 2007.

[7] S. Jafar and S. Shamai, "Degrees of Freedom Region of the MIMO X Channel," *IEEE Transactions on Information Theory*, vol. 54, no. 1, pp. 151–170, 2008.

[8] K. Gomadam, V. Cadambe, and S. Jafar, "A Distributed Numerical Approach to Interference Alignment and Applications to Wireless Interference Networks," *IEEE Transactions on Information Theory*, vol. 57, no. 6, pp. 3309–3322, June 2011.

[9] D. Papailiopoulos and A. Dimakis, "Interference Alignment as a Rank Constrained Rank Minimization," in *Proc. of IEEE Global Telecommunications Conference (GLOBECOM)*, Miami, FL, Dec 2010.

[10] H. Viswanathan, E. K. Lee, I. Rodero, and D. Pompili, "An Autonomic Resource Provisioning Framework for Mobile Computing Grids," in *Proc. of IEEE International Conference on Autonomic Computing (ICAC)*, San Jose, CA, Sept. 2012.

[11] M. Stojanovic, "On the Relationship Between Capacity and Distance in an Underwater Acoustic Communication Channel," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 11, no. 4, pp. 34–43, Oct. 2007.

[12] C. Wang, E. Au, R. Murch, W. Mow, R. Cheng, and V. Lau, "On the Performance of the MIMO Zero-Forcing Receiver in the Presence of Channel Estimation Error," *IEEE Transactions on Wireless Communications*, vol. 6, no. 3, pp. 805–810, 2007.