A Parallel Decoding Approach for Mitigating Near-Far Interference in Internet of Underwater Things

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Abstract—With the massive development of underwater small robotic vehicles and matching acoustic modems, applications for Internet of Underwater Things (IoUT) are emerging. IoUT involves communication between non-synchronized network nodes organized in a mesh. A limiting factor of such communication is the so-called near-far effect, where transmissions from a node (near) close to a common receiver blocks the transmissions of a farther node (far). Due to the high-power attenuation in the underwater acoustic channel, near-far is common in underwater acoustic communication networks, and the phenomena occurs even for a distance ratio of 80% between the near and far nodes to the receiver, and the large number of nodes in IoUT compounds the effect of this phenomena. While current approaches only consider the jamming effect to the far signal, in this paper, we consider cancelling the interference from both sources by estimating and equalizing the channels on parallel, thereby significantly improving the decoding of both signals. As a result, the IoUT can function much better. To limit mutual interference, we propose an automatic switching mechanism that controls the cancellation operation both in channel estimation and channel equalization. Simulation results show that our approach obtains significant improvement for communication from both near and far nodes. Results from a designated sea trial demonstrate that when both nodes are affected by their mutual transmissions, our proposed method improves the output signal-to-noise ratio (SNR) significantly.

Index Terms—Internet of underwater things, Underwater acoustic communications, near-far interference, interference cancellation, compressed sensing, multiuser detection, Signal separation and interference rejection, diversity techniques and equalization.

I. INTRODUCTION

With the current boost of available underwater acoustic communication capabilities and the increase of low cost underwater robotic vehicles, a multitude of applications have emerged for underwater network communications. Among these are the Internet of Underwater Things (IoUT) [1] comprised of a large number of sensor devices aimed for oceanographic data collection (such as temperature, salinity, conductivity, dissolved oxygen, and etc.), ocean environmental monitoring, oil or mineral extraction, communication between autonomous submerged vehicles, and communication between groups of scuba divers performing subsea maintenance [2], [3].

One main capability required for IoUT is the communication within its devices.

As shown in the illustration in Fig. 1, the IoUT’s devices are considered arranged in a mesh network of non-synchronized nodes deployed at different times and in a large area. Due to this random-like deployment, a common challenge in IoUT applications is how to deal with joint interference from signals received simultaneously by a common receiver [1]. Since the UAC bandwidth is limited, the data rate is extremely low and the reception is mostly performed in an omni-directional manner (i.e., no directivity is applied in reception). As a result, the signal level is low and interfering signals cause collisions and data loss. Considering the low available bandwidth of underwater communications and that the receiver is often unaware of the transmitting nodes’ location, solutions such as frequency separation of interfering transmissions [4] or adaptive transmission power control [5] may not be the best option. Instead, underwater networks manage such interference by employing interference-free scheduling protocols [6]–[8].
spatial diversity [9], [10], interference alignment [11], [12], orthogonal signals [13] or interference rejection [14]. In contrast to the former approaches, interference rejection approach does not require collaboration between the network nodes, and is thus our choice.

In this paper, we focus on the so-called near-far problem for IoUT, where nodes are spread in space such that colliding packets may be resolved for a source located close to the receiver, but not for a farther node for which the signal-to-interference-plus-noise ratio (SINR) is low. Here, the closer source to the receiver is often called the jamming or near node, while the farther node is called the jammed or far node. For example, in Fig. 1, a diver and a remote operated vehicle transmit message to a autonomous underwater vehicle simultaneously, because the diver is further to the AUV, thus interference occurs. In underwater acoustic communication, due to the high dependency of the power attenuation in range, the near-far problem exists even for a range ratio of 80% between the jamming-receiver range and the jammed-receiver range, and the problem compounds as the IoUT grows. Naturally, this phenomenon limits the performance of network applications, causing dropped packets and increased delays.

While in some cases, near-far situations cause diversity and thus can be viewed as a network resource to assist network operations [15], [16], this phenomena is commonly regarded as a source of interference that should be resolved - either in the media access control (MAC) layer or in the physical layer of the communications stack. In the context of MAC scheduling, the near-far problem is viewed as a source of secondary conflicts [17], where the network should try to avoid in the first place. The solution thus involves identifying a near-far scenario as part of the topology-discovery process. In [18], near-far situations are identified by non-symmetric components in the network topology matrix, which basically means there is a jammed node in the network. In [19], near-far collisions are identified by the common receiver based on the parts of the signals that do not collide. This approach is practical, due to the long propagation delay in underwater acoustic communication, there is a very low chance of completely overlapping receptions. In [20], expected near-far collisions are identified prior to transmissions based on acoustic propagation models, assuming location prior knowledge of the nodes. Once a near-far is identified, the scheduling solution is altered by setting proper constraints for the selected transmission schedule, such that the jamming and jammed nodes avoid transmitting together [21], or the near node is instructed to adjust its power to avoid the jamming altogether [22].

In the physical layer, near-far situations are solved through filtering. The most common is the noise-canceling filter, where the strong signal is first resolved and then removed from the received signal to allow the decoding of the jammed signal. To this end, a synthetic version of the resolved strong signal is used as a reference. This signal passes through a filter and then is subtracted from the received signal. The filter adapts iteratively by minimizing the output of the noise cancellation filter [23]. For underwater acoustic communication, in [14], this approach has been extended to direct the adaptive filter to identify only the strong signal, thereby reducing the effect on the jammed signal. Multiuser interference suppression has also been applied in the context of equalization, where interferes are treated as residuals from the channel estimation process [24] by iteratively resolving inter-block interferes [25], or by means of interference alignments [11]. In all these cases, the decoding is performed successively under the assumption that the jamming signal can be correctly resolved. While this can be assumed in some cases, mostly the near-far situation is not conclusive, meaning that the jamming signal also experiences interference.

Parallel decoding has been offered before. For example, in [26] a parallel interference cancelation scheme for CDMA uses tentative decision devices to produce estimated received data for generation and cancellation of mutual interference. Also for CDMA, [27] proposed an adaptive multistage parallel interference cancellation method where interference rejection is performed using least mean squares. Yet, spectral efficiency of CDMA is low and does not fit the extended capacity in IoUT networks. In [28] and [29], a simultaneous cancelling of multiuser interference is obtained by time reversal and directed adaptive decision feedback equalizer. However, calibrating the equalizer requires careful tuning of the parameters of the equalizer and phase tracker, which makes the system sensitive to channel instabilities. Instead, our method performs the channel estimation along side interference rejection thereby achieving robustness to various channel structures.

The case of near-far interference holds similarities to co-channel interference in the framework of multiple-input-multiple-output (MIMO) communication. Here, signal from one transmitter is corrupted by the other, estimating and equalizing the channels of both the jammed and jamming nodes are great challenges. For underwater acoustic MIMO communication, the interferences are removed only during channel equalization. For example, in [30], space-time trellis coding method was used to remove interference, and the channel estimation method was traditional minimum mean square error (MMSE). Similarly, [31] and [32] proposed a successive interference cancellation combined with Turbo equalization. Relying on the sparseness of the underwater acoustic channel's impulse response, in [33], we proposed a distributed compressed sensing method to suppress the interference during channel estimation.

Different than what we presented in [34] for underwater acoustic MIMO communication, in this work we focus on the suppression of both strong interference (for the far node decoding branch) and weak interference (for the close node decoding branch). Further, unlike [34], here we also focus on the cancelling of interference during channel estimation. In contrast to current approaches that perform interference cancellation (IC) successively, our approach performs the decoding in parallel. This not only provides benefits in terms of latency, it also enables better decoding of the near signal and far signal. In [35], we introduced a parallel decoding method for near-far problem using CE-DFE. In this work, we extend this work by introducing the theory behind setting the IC filter’s coefficient, adding interference rejection also
at the channel estimation step to handle inaccuracy already in the equalization step, as well as an automatic switching mechanism based on a diversity factor to control the operation of the IC in cases where interference rejection actually damage performance or not needed. Finally, beyond the work in [35], in this paper we extend the simulation analysis to include successive decoding as benchmark, and also show results from several sea experiments demonstrating the applicability of our approach in real conditions.

The novelty of our work is by introducing two new components: 1) an iterative IC during channel estimation that has the ability to remove the interference by projecting the received signal to a new subspace, and 2) a switching mechanism to suppress signal distortion when IC is not required for channel equalization during near-far situations. For this, we introduce a new decoding structure that cancels interference not just for the weak signal but also for the strong one. In particular, the cancellation is performed by sharing the output of the decoding process across the channel estimation and channel equalization branches. As a result, our approach is the first to combat dynamic near-far scenarios as expected in an IoUT. That is, we consider not just the case of a very close and very far transmitters, but also the common case where the range difference between the near and far nodes is not dramatic but a near-far interference still exists. We analyze the performance of our algorithms in numerical simulations and demonstrate its practicality in a designated sea experiment. Compared to our previous approach in [34], and to the successive IC benchmark scheme [24], the results show that our proposed methods obtains higher output SNR for both the jammed and jamming signals. The contribution of this paper is thus threefold:

1) We derive filter coefficients for CE-DFE specifically tailored to cancel to interference affecting multiple channel taps as in the underwater channel.
2) A novel design of channel estimation with interference cancellation.
3) An automatic switching mechanism to control interference rejection activated by a diversity factor only when interference are expected to effect performance.

The remaining of this paper is organized as follows. Section II describes the channel model. In Section II, we present the system model. In Section III, our parallel IC channel estimation and channel equalization schemes, as well as IC switching mechanism are described. Section IV provides simulation results and sea trial results. Finally, concluding remarks are drawn in Section V. The following notations are used in this paper. Boldface uppercase letters and boldface lowercase letters denote matrices and column vectors respectively. Superscripts $(\cdot)^T$, $(\cdot)^*$, and $(\cdot)^H$ denote transpose, conjugation, and Hermitian transpose respectively. Notation $I$ denotes the identity matrix. Notation $A(:,j)$ denotes the $j$-th column of matrix $A$. Notation $\|\cdot\|_2$ denotes Euclid norm. Notation $E$ denotes the expectation. Notation $\otimes$ denotes convolution.

II. System Model

Fig. 1 shows a diagram of an IoUT. The system includes acoustical devices such as autonomous underwater vehicles, remote operated vehicle, scuba divers, underwater drifters, and fixed submerged stations, which exchange data in a mesh-like network. When more than one device transmits simultaneously, mutual interference may arise at a common receiver. Referring to the example in Fig. 2, there are two transmitters $Tx_1$ and $Tx_2$ to a common receiver with the distances of $d_1$ and $d_2$ respectively. If $d_1 > d_2$, most likely, the SNR for the signal from $Tx_1$ is smaller than that from $Tx_2$. The SNR is defined by

$$\gamma_i = \frac{||s_i||^2}{||w||^2_2},$$

(1)

where $s_i$ is the desired signal, i.e., the signal that decoder currently tries to demodulate from the $i$-th transmitter, and $w$ is the ambient noise. Another measure of interest is the signal-to-interference-plus-noise ratio (SINR), defined by

$$\rho_i = \frac{||s_i||^2}{||s_j||^2 + ||w||^2_2},$$

(2)

where $i \neq j$. When $\rho_1 < \gamma_1$, the transmission from $Tx_1$ is jammed by the transmission from $Tx_2$. Such a case is illustrated in Fig. 2, where between time instances $t_2$ and $t_3$, an overlap occurs and the farther node may be jammed. In underwater acoustic communication, due to the low transmission rate and the long propagation delay, this scenario is common.

In the case described above, the traditional way to decode the message would be to first decode the signal with the high SINR, followed by the signal with the low SINR. We call this the successive interference cancellation (SIC) approach. However, such an approach fails to consider interference coming from the farther node. While these interferences are weaker relative to the opposite case, they may still degrade the communication performance of the stronger signal. Furthermore, such interference may reduce the accuracy of channel estimation for the strong signal, and affect the accuracy in the second stage. In this paper, we address this problem by proposing a parallel decoding scheme for mitigating near-far problems in underwater acoustic communications networks with the aim of improving detection performance for both the jamming and the jammed nodes. In our system model, we assume that the transmitted sequence is independent and identically distributed (i.i.d.), and is normalized prior to decoding. We also assume that the channels from the two transmitting sources are statistically independent.
A. Structure of Scheme

The structure of our receiver is illustrated in Fig. 3. Our method works in the framework of two CE-DFEs. For each CE-DFE, there are two stages, one channel estimator and one decision feedback equalizer. Before channel estimation, there is a switch which determines whether it needs IC. The channel estimator can be implemented by orthogonal matching pursuit (OMP) [36]. Notation $h_{Tx_1}$ and $h_{Tx_2}$ are the channel estimates. Filters $g_{ff}$ and $g_{fb}$ are the feedforward and feedback filters, respectively. Filter $g_{ic}$ is the IC filter whose purpose is to mitigate the interferences. The filters $g_{ff}$, $g_{fb}$, and $g_{ic}$ are measured by channel estimates.

As we clarify further below, the channel estimation IC filter requires knowledge of the transmitted signal to allow IC before channel estimation. After training mode, this information is obtained iteratively as a feedback from the decoding output. In other words, the output of equalizer will be re-used for channel estimation and interference cancellation. For this, we introduce a delay operation, represented by $z^{-1}$ operator in Fig. 3. Since the two IC filters may corrupt the signal and thus degrade performance when no interference exists, we operate both $g_{ic}$ only when interference is detected. To this end, we employ a switch before each IC operation. For each decoding branch, the logic that operates the switches is the same for channel estimation and channel equalization. For each CE-DFE in Fig. 3, the first step is channel estimation, and then the filters of the DFE are obtained based on the channel estimate, it is a successive process. However, for each CE-DFE, they will work simultaneously both for decoding near and far nodes, this is why we call our method as parallel decoding, while in successive method, it decodes near node first, and then decodes far node. In the following, for clarity we derive our solution for two transmitting sources. This approach can be straightforward extended to the case of multiple transmitters.

III. OUR PARALLEL IC APPROACH

B. Signal Representation

Denote $y(i)$ as the received signal, $x_1(i)$ and $x_2(i)$ as the transmitted message from $Tx_1$ and $Tx_2$, denote $h_{Tx_1}(i)$ and $h_{Tx_2}(i)$ as the channels from $Tx_1$ and $Tx_2$, respectively. The mutual interferences are modeled by the binary operators $K_1$ and $K_2$ for the two transmitting sources, respectively. Considering a linear channel model, the received signal $y(i)$ can be written as

$$ y(i) = K_1 \sum_{l=0}^{L-1} x_1(i-l) h_{Tx_1}(l) + K_2 \sum_{l=0}^{L-1} x_2(i-l) h_{Tx_2}(l) + w(i), $$

where $w$ is the ambient noise. In the example in Fig. 2, $K_1 = 1$, $K_2 = 0$ when $t_0 \leq t \leq t_1$, $K_1 = 1$, $K_2 = 1$ when $t_1 \leq t \leq t_2$, and $K_1 = 0$, $K_2 = 1$ when $t_2 \leq t \leq t_3$. Notation $\leq$ is defined as the length of channel impulse response.

Collecting a time window of $y(i)$ observation, we obtain

$$ y = K_1 (G_1 x_1) + K_2 (G_2 x_2) + w, $$

where $G_1$ and $G_2$ are the channel matrices from the two sources, and $w$ is the ambient noise. Notations $y$, $x_1$, $w$, and $G_1$ are defined as follows

$$ y \triangleq (y(i + L_c) \cdots y(i) \cdots y(i - L_a + 1))T, $$

$$ x_1 \triangleq (x_1(i + L_c) \cdots x_1(i) \cdots x_1(i - L_a + 1))T, $$

$$ w \triangleq (w(i + L_c) \cdots w(i) \cdots w(i - L_a + 1))T, $$

$$ G_1 \triangleq \begin{bmatrix} h_{Tx_1}(0) & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & h_{Tx_1}(L-1) & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & h_{Tx_1}(0) & \cdots & h_{Tx_1}(L-1) \end{bmatrix}. $$
\[ G_1 = \langle G_0, \mathbf{g}_1 | F_1 \rangle . \]  
(9)

\( x_2 \) and \( G_2 \) have a similar structure as \( x_1 \) and \( G_1 \), respectively. In (5), (6), and (7), \( L_c \) and \( L_a \) denote the number of causal and a-causal taps, respectively.

### C. Channel Equalization

According to Fig. 3, when both \( K_1 \) and \( K_2 \) are 1 and the two switches are closed, \( x_{s_1} (i) \) and \( x_{s_2} (i) \) can be represented by

\[ x_{s_1} = g_{ff}^H y + g_{ff}^H x_{fb} + g_{ic}^H x_{fb_2} , \]  
(10a)

\[ x_{s_2} = g_{ff}^H y + g_{ff}^H x_{fb_2} + g_{ic}^H x_{fb_1} , \]  
(10b)

The lengths of \( g_{ff} \), \( g_{fb} \), and \( g_{ic} \) are \( L_{ff} \), \( L_{fb} \), and \( L_{ic} \), respectively. We partition the transmitted symbols into three groups \( x_m \) be canceled by the IC filter, and the additional terms \( \mathbf{x}_{fb_m} \) from \( \mathbf{F}_m \) in (11) is the portion of the received signal which can be canceled by the feedback filter. The terms \( \mathbf{G}_{m} \) are partitioned into three groups shown in (8). Then (4) can be written as

\[ y = K_1 g_{ff}^H x_{fb_1} + \mathbf{F}_1 x_{fb_1} + G_{0_1} x_{0_1} + \mathbf{w} . \]  
(11)

We discuss the received signal under two scenarios.

**I.** \( K_1 = 1 \) and \( K_2 = 0 \), or \( K_1 = 0 \) and \( K_2 = 1 \):

1. In this case, there is no interference. The term \( g_{ff}^H x_{fb_1} \) in (11) is the portion of the received signal which corresponds to the transmitted signal that needs to be recovered. The term \( \mathbf{F}_1 x_{fb_1} \) in (11) is the portion signal, which can be canceled by the feedback filter. The terms \( G_{0_1} x_{0_1} \) and \( \mathbf{w} \) are the effective observation noise that the feedforward filter must try to eliminate.

**II.** \( K_1 = 1 \) and \( K_2 = 1 \):

1. In this case, interferences exist for both near and far nodes. When decoding \( \mathbf{T}_X \), the signal from \( \mathbf{T}_X \) is considered as the interference, and vice versa when decoding \( \mathbf{T}_X \). In order to recover the transmitted symbols from \( \mathbf{T}_X \), interference terms \( \mathbf{F}_2 \) and \( x_{fb_2} \) in (11) should be canceled by the IC filter, and the additional terms \( g_{ff}^H x_{fb_2} \), \( g_{ic}^H x_{fb_2} \), and \( \mathbf{w} \) in (11) should be mitigated by the feedback filter. Also, it is necessary to perform IC before channel estimation to improve channel estimation performance.

Based on the model in Fig. 3, the soft output can be described by

\[ x_{s_m} = \mathbf{d}_m^H \mathbf{u}_m , \]  
(12)

where

\[ \mathbf{d}_m = (g_{ff}^H, g_{fb}^H, \mathbf{g}_{ic}^H)^H , \]  
(13a)

\[ \mathbf{u}_1 = (y^H, x_{fb_1}^H, x_{fb_1}^H)^H , \]  
(13b)

\[ \mathbf{u}_2 = (y^H, x_{fb_2}^H, x_{fb_2}^H)^H . \]  
(13c)

To obtain the feedforward filters, feedback filters, and IC filters, we solve the reconstruction problem as:

\[ \hat{\mathbf{d}}_m = \arg \min_{\mathbf{d}_m} \mathbb{E} \left( \left| \mathbf{d}_m^H \mathbf{u}_m - x_m(i) \right| ^2 \right) , \]  
(14)

We adopt the linear minimum mean square error method to obtain the optimal filters, the optimal filters can be expressed as

\[ \hat{\mathbf{d}}_m = \mathbf{R}^{-1}_m \mathbf{r}_{x_m}, \]  
(15)

where

\[ \mathbf{R}_{x_m} = \mathbb{E} \left( \mathbf{u}_m \mathbf{u}_m^H \right) , \]  
(16a)

\[ \mathbf{r}_{x_m} = \mathbb{E} (x^H (i) \mathbf{u}_m) . \]  
(16b)

To derivation of \( \mathbf{R}_{x_m} \) and \( \mathbf{r}_{x_m} \), we refer the reader to [34].

Finally, the coefficients of the filters are measured as (see [34] for complete derivations)

\[ g_{ff_m} = (K_1 (g_{ff}^H + 1) + K_2 (g_{22}^H + \mathbf{D}_2))^{-1} g_m , \]  
(17a)

\[ g_{fb_m} = -K_m \mathbf{F}_m g_{ff_m} , \]  
(17b)

\[ g_{ic_m} = -K_m (\mathbf{F}_m + 1) g_{ff_m} . \]  
(17c)

where \( m = 1, 2 \), and \( \mathbf{D}_m = \mathbf{R}_u + G_{0_m} G_{0_m}^H \). \( \mathbf{R}_u \) is the covariance of noise.

### D. Channel estimation with interference cancellation

While, commonly, IC is performed during the decoding process, in some cases the interferences from the far signal are high such that channel equalization fails. For these cases, we aim to perform IC already in the channel estimation phase. In that context, our goal is to interleave channel estimations across the near and far branches such that IC can be achieved. Referring to Fig. 3, in CE-DFE this interleaving is performed by feeding the outputs from the equalization and decoding process of both branches.

1. **Signal’s Projection:** Consider the channel model in (3), and assume the channel is time-invariant over a number of \( S \) samples. For channel estimation, we collect number of \( S \) received signal into a vector,

\[ y = K_1 \mathbf{A}_1 h_{x_1} + K_2 \mathbf{A}_2 h_{x_2} + \mathbf{w} , \]  
(18)

where

\[ \mathbf{A}_1 = \left( \begin{array}{ccc} x_1(L - 1) & x_1(L - 2) & \cdots & x_1(0) \\ x_1(L) & x_1(L - 1) & \cdots & x_1(1) \\ \vdots & \vdots & \ddots & \vdots \\ x_1(L + S - 2) & x_1(L + S - 3) & \cdots & x_1(S - 1) \end{array} \right) , \]  
(19)

\[ y = (y(L - 1) \ y(L) \ \cdots \ y(L + S - 2))^T , \]  
(20)

\[ h_{x_1} = (h_{x_1}(L - 1) \ h_{x_1}(L - 2) \ \cdots \ h_{x_1}(0))^T , \]  
(21)

and similar for the second branch with matrix \( \mathbf{A}_2 \) and vector \( \mathbf{h}_{x_2} \).

Traditionally, during the estimation of \( \mathbf{h}_{x_1} \), the interference term \( \mathbf{A}_2 \mathbf{h}_{x_2} \) in (18) is treated as noise, which degrades the accuracy of the channel estimation in cases of near-far problem. Utilizing the fact that the underwater acoustic channel is sparse which may improve performance by using compressed sensing channel estimation method such as OMP and its variants. The compressed sensing methods track the non-zero taps to suppress some of the interference. However,
here strong near-far interference may not allow the lock onto the significant channel taps, and erroneous taps will propagate to the next iteration.

Another IC approach for near-far scenarios is the SIC approach, where firstly the channel with the high SNR is estimated and the received signal is reconstructed via $A_1 h_{Tx_1}$. Then, the reconstructed signal is subtracted from received signal to allow channel estimation for the weak signal. However, as we show in our results below, in a non-negligible number of cases, the weak signal also affects the accuracy of channel estimation for the strong signal leading to error propagation, and also for the decoding of the weak signal. We therefore propose an IC filter positioned prior to the channel estimation operation.

The intuition behind our method is that, when both strong and weak signals are decoded in parallel, the unknown interfering factor in each decoding branch is the channel impulse response of the other branch. Hence, we use a projection matrix to span the received signal to a new subspace. In particular, to estimate $h_{Tx_1}$, we project (18) to a subspace whose basis is orthogonal with $A_2$, and vice versa for $h_{Tx_2}$.

In [37], a projection matrix was used to suppress the side-lobe, this approach can be used also here for channel estimation with IC. The projection matrices are defined as

$$P_2 \triangleq I - K_2 A_2 (A_2^H A_2)^{-1} A_2^H,$$  \hspace{1cm} (22a)

$$P_1 \triangleq I - K_1 A_1 (A_1^H A_1)^{-1} A_1^H.$$  \hspace{1cm} (22b)

To calculate $P_2$ and $P_1$, during training mode, sequences $A_1$ and $A_2$ are known in advance, after training mode we employ an iterative procedure such that $A_1$ and $A_2$ are chosen as the output of the decoding procedure for the decoding of $x_1$ and $x_2$ branches. For this reason, we employ a delay of certain samples during channel estimation. Naturally, such a delay may introduce inaccuracies for time-varying channels. In these cases, the buffering of $y$ can be performed on overlapping time windows.

In order to estimate $h_{Tx_1}$, (18) can be written as

$$P_2 y = K_1 P_2 A_1 h_{Tx_1} + K_2 P_2 A_2 h_{Tx_2} + P_2 w,$$

$$= K_1 P_2 A_1 h_{Tx_1} + P_2 w,$$  \hspace{1cm} (23)

where the right-hand side equality is straightforward when plugging $P_2$ over the $A_2$ component. Note that by this projection, the unknown channel impulse response part $h_{Tx_2}$ is canceled, leaving (23) with only the unknown $h_{Tx_1}$ component to be estimated. Further, (23) can be written as

$$p_{y_1} = K_1 \Phi_1 h_{Tx_1} + p_{w_1},$$  \hspace{1cm} (24)

where $p_{y_1} \triangleq P_2 y$, $\Phi_1 \triangleq P_2 A_1$, and $p_{w_1} \triangleq P_2 w$. Similarly, to estimate $h_{Tx_2}$, after projection operation we obtain

$$p_{y_2} = K_2 \Phi_2 h_{Tx_2} + p_{w_2},$$  \hspace{1cm} (25)

where $p_{y_2} \triangleq P_1 y$, $\Phi_2 \triangleq P_1 A_2$, and $p_{w_2} \triangleq P_1 w$. Once the projection is successfully applied, least square or OMP algorithm can be directly used.

2) Model error analysis: We now analyze the performance of our IC channel estimation model. Consider without loss of generality for the estimation of $h_{Tx_1}$, define the traditional channel model error by

$$e_{tr_1} = \|y - A_1 h_{Tx_1}\|^2_2$$

$$= (y - A_1 h_{Tx_1})^H (y - A_1 h_{Tx_1})$$

$$= y^H y - y^H A_1 h_{Tx_1} - h_{Tx_1}^H A_1^H y + h_{Tx_1}^H A_1^H A_1 h_{Tx_1}.$$  \hspace{1cm} (26)

Similarly, the proposed channel model error for estimating channel $h_{Tx_1}$ is defined by

$$e_{pr_1} = \|y - \Phi_1 h_{Tx_1}\|^2_2$$

$$= (P_2 y - P_2 A_1 h_{Tx_1})^H (P_2 y - P_2 A_1 h_{Tx_1})$$

$$= y^H P_2^H P_2 y - y^H P_2^H P_2 A_1 h_{Tx_1} - h_{Tx_1}^H P_2^H P_2 A_1^H y + h_{Tx_1}^H P_2^H P_2 A_1^H A_1 h_{Tx_1}.$$  \hspace{1cm} (27)

We assume $A_2(:,i) A_2(:,j) = b_{ij}$, which is the $(i,j)$-th element of matrix $A_2 A_2^H$, where $i \neq j$, and $A_2(:,i) A_2(:,j) \approx (S\epsilon)$ when $i = j$, and $\epsilon$ denotes the energy of one transmitted bit. Following our assumption that the transmitted sequence is i.i.d, we obtain $(b_{ij}) \ll (S\epsilon)$ and $(b_{ij})/(S\epsilon) \approx 0$. Thus, we get $A_2^H A_2 \approx (S\epsilon) I$. Similarly, we also get $A_2^H A_2 \approx (L\epsilon) I$. As a result,

$$A_2 (A_2^H A_2)^{-1} A_2^H \approx \frac{L}{S} I,$$  \hspace{1cm} (28)

and

$$P_2 \approx \frac{S - L}{S} I.$$  \hspace{1cm} (29)

Note that, in (29), $S$ should be larger than $L$, otherwise the approximation fails.

Based on (26) and (27), we conclude that

$$e_{pr_1} \approx \left( \frac{S - L}{S} \right)^2 e_{pr_2} < e_{tr_1},$$  \hspace{1cm} (30)

such that $e_{pr_2} < e_{tr_2}$. That is, using our projection method, the accuracy of the channel estimation increases. Also note that, as $S$ approaches infinity, $e_{pr_m} = e_{tr_m}$, which means that the training length should be large enough relative to channel length to suppress the interference for the traditional channel model.

3) Computational complexity analysis: Compared with the traditional channel model, our IC method applies extra complexity to the process of channel estimation. This involves the construction of the projection matrices and several matrix left multiplications. Specifically, the extra computational complexity is caused by the calculation of $P_m = I - A_m (A_m^H A_m)^{-1} A_m^H$, a $P_m$ left multiplying by received signal ($P_m y$), and a $P_m$ left multiplying of the training matrix ($P_m A_m$). Because of the limited bandwidth for underwater acoustic channels, usually the dimension of the channel model is small, so the extra computational complexity is negligible.

As we show in Section IV below, results that our method achieves high performance gain in low SINR and performance do not decrease for high SINR. Hence, we argue that this complexity addition is justified.
E. Strategy for Operating the IC Switches

We now discuss the control over the IC switches. A possible metric to open/close the IC switches is the SINR defined in (2). This is because the strength of the interference is the direct reason for the need for IC. However, the SINR does not take into account the structure of the channel impulse response. Instead, to set a strategy to operate the IC switches, we are motivated by [38] which investigated the DFE’s performance according to the number of receivers, the separation of receivers, and the array aperture size. Because underwater acoustic channel is a time and frequency selective channel, to improve the communication performance, vertical arrays are often used on the receiver side to exploit the diversity gain, that is the gain obtained from differences between different channel impulse responses. For example, in [38] and [31], multiple channel DFE are used, and in [28] and [29] multiple channels based time reversal are adopted. In [38] it indicated that the spatial diversity affected the multichannel equalizer’s performance. Following this observation, we consider the spatial diversity factor (SDF) defined by

\[
\kappa = \max \left( \sum_{m=1}^{M} h_m(t) \otimes h_m^*(-t) \right),
\]

where \(h_m(t)\) is the channel estimate for the \(m\)-th hydrophone. Theoretically, if the number of receiving nodes in a vertical array are sufficient and the channel estimates \(h_m(t)\) are accurate, the term \(\sum_{m=1}^{M} h_m(t) \otimes h_m^*(-t)\) will approximate the \(q(t)\) function [39]. Yet, practically, the number of receiving nodes is limited and the channel estimates contain much noise because of the mutual interference. Hence, many sidelobes exist and the main peak of \(\sum_{m=1}^{M} h_m(t) \otimes h_m^*(-t)\) decreases. Equation (31) denotes the value of main peak in the latter term, and can thus be roughly understood as the spatial diversity gain of a vertical array.

As an indicator metrics, in our simulation, we directly use a channel estimation algorithm to obtain \(h_m(t)\), thereby calculating \(\kappa_{Tx1}\) and \(\kappa_{Tx2}\). This yields the ratio \(\text{SDFR}_{Tx1} = \frac{\kappa_{Tx1}}{\kappa_{Tx2}}\), which denotes the spatial diversity factor ratio (SDFR) between the Tx1 signals and Tx2 signals. In real deployment as we did during our sea trial, instead of a prior knowledge of \(h_{Txk}\), we use the preamble from the first arrival and the postamble from the last arrival to measure \(h_m(t)\) and to obtain the SDFR. In the following, we use notations \(\kappa_S\) and \(\kappa_W\) to denote the SDF from the strong and the weak signals respectively. To set the ratio between the above SDFs when to open/close each switch, we use a threshold TH, which can be set through Monte-Carlo simulations.

We consider the two cases:

**Case 1:** \(\kappa_S/\kappa_W < \text{TH}\)

In this case, both the near and far nodes suffer from interference of the same order of magnitude. We demonstrate the case by three time instances presented in Fig. 2. Between \(t_1\) and \(t_2\), there is only one transmitted signal at the receiver end; thus, only one DFE and one channel estimator in Fig. 3 work. In this case, there is no interference to be cancelled, so the switch in channel estimator or DFE should open. That is, between \(t_1 - t_2\) in Fig. 2, only DFE1 works, and the IC is inactive. In contrast, between time instances \(t_2\) and \(t_3\), signals from both the near and the far node arrive, and significant interferences exist for both nodes. Here, for each channel estimator, interference from the other transmitter should be canceled, and the two switches are closed to allow IC. This case where the time instances between \(t_3 - t_4\) is similar for the time frame between \(t_1 - t_2\).

**Case 2:** \(\kappa_S/\kappa_W \geq \text{TH}\)

In this case, only the weak signal should be considered for interference rejection. Here, the signal level from the near node is much higher than that from the far node. As a result, the traditional channel estimation for the near node is much more accurate than that of the far node. Thus, the filter coefficients in (17) obtained by the channel estimates of the weak and strong signals would introduce noise. Moreover, because of the far node’s low SNR, the output which provides the interference to be removed for the near node is not accurate, therefore the communication performance for the near node degrades. On the other hand, because the channel estimation for the near signal is accurate, the interference at the weak signal’s branch would also produce an accurate estimation, and the DFE of the weak signal’s branch would benefit from the IC operation leading to performance upgrade. We therefore close the IC switch involving the DFE branch that decodes the weak signals, and open the IC switch for the DFE branch that decodes the strong signal. We note that in this case, besides the IC operation prior to the channel estimation, our scheme becomes the same as the SIC scheme.

F. Discussion

Note that different than other filtering schemes for IC such as our previous work in [14] or interference alignment approaches such as in [11] that assumes orthogonality of the transmitted signals or of the two channel impulse responses, to obtain (24) and (25) we do not require such strong assumptions. As a result, our method does not require coordination between the different transmitters and is not limited to spatial dependent channels. This is also the reason that our approach is scalable to removing interference from multiple transmitters. Still, our approach cannot handle the special case of \(A_1 = A_2\), since then, neglecting the noise term, the right-hand of (24) and (25) are 0. We also note that, as illustrated in Fig. 3, the switching mechanism allows adaptation of the solution. Specifically, if there is no interference, the switches are open \((K_1 = 0\text{ or }K_2 = 0)\), and the projection \(P_1\) or \(P_2\) becomes the identity matrix. That is, no projection operation is performed.

IV. RESULTS AND ANALYSIS

In this section, we explore the performance of our parallel IC approach. We consider both the performance of channel estimation and of channel equalization. We make the following notations: Our parallel channel equalization with IC is denoted as PIC, the successive channel equalization denoted as SIC, and the channel equalization without IC is denoted as NoIC. In case IC is interleaved with OMP, the method is referred to as OMP-IC, otherwise OMP with no IC is denoted by OMP-NoIC. We compare the following receivers, the first three are versions of our scheme and the last two are benchmarks:
1) PIC/OMP-IC: Both channel equalization and channel estimation have IC components for CE-DFE.
2) PIC/OMP-NoIC: Only channel equalization contains IC components for CE-DFE.
3) NoIC/OMP-IC: Only channel estimation contains IC components for CE-DFE.
4) SIC/OMP-NoIC (benchmark) Successive receiver that decodes strong signal first, and then decodes weak signal and removes IC caused from strong signal [24].
5) NoIC/OMP-NoIC (benchmark) Traditional CE-DFE without IC for both channel estimation and channel equalization.

Results are compared in both simulations and sea trial.

As a quality metric, to evaluate the performance of channel estimation in simulation, we use the mean square error (MSE) defined by

\[
MSE = \| h - \hat{h} \|_2^2,
\]

where \( h \) and \( \hat{h} \) are the known channel and channel estimate, respectively. We also consider the output SNR to evaluate the communication performance. The output SNR is measured at the input of the decision-making block and is defined by

\[
\tau = \frac{\| x \|_2^2}{\| x - x_b \|_2},
\]

where \( x \) is the transmitted symbols, and \( x_b \) is the soft output from DFE receiver.

A. Numerical Simulation

1) Simulation Setup: Our simulation setup includes two transmitting nodes with a single transmitter, and a receiver array that contains four receiving elements. In each Monte-Carlo simulation run, the location of one of the transmitters which is denoted as \( T_x_1 \) is fixed at 1000 m from the receiver, while the location of the second transmitter which is denoted as \( T_x_2 \), is chosen uniformly and randomly with its range from the receiver between 2000 m and 100 m. The distances between \( T_x_1 \) and \( T_x_2 \) to the receiver are denoted by \( d_1 \) and \( d_2 \), respectively. The depths of the four receiving elements are 4 m, 8 m, 12 m, and 16 m, while the transmitters’ depths are fixed at 8 m. The two sources transmit equal packets of 134320 bits with different message. The symbol rate is 6,000 symbols/s. The packets are scheduled such that overlapping always occurs.

To generate the propagation delay and channel impulse response for the near-receiver and far-receiver links, we use the Bellhop ray-tracing software package [40]. A flat ocean is assumed with a constant sound speed profile at 1,500 m/s and a constant water depth of 20 m. For each location setup, the transmitted signals are convoluted with the corresponding channel. An example of two such channels is shown in Fig. 4 for two transmitters located 1000 m and 500 m from the common receiver. In this example, the delay spread is roughly 40 ms, and typical sparse is observed. As expected, the channels are quite different.

2) Simulation Results: Fig. 5 depicts the relationship between the MSE with the SINR (Fig. 5(a)) and the training length (Fig. 5(b)). Here, we consider \( T_x_1 \) and \( T_x_2 \) located 1000 m and 800 m from the receiver, respectively. The training length is set to 115 ms. As expected, when the interference level is high, the MSE is inversely proportional to the SINR. Comparing performance of OMP channel estimation with IC which is denoted as OMP-IC, to that without IC which is denoted as OMP-NoIC, we observe a significant gain when the SINR is low. In particular, for very low SINR as in the near-far scenario, the gain is roughly 20 dB. We observe that, when the SINR is low, the gain obtained by OMP-NoIC is higher than by OMP-NoIC. This is because of OMP-NoIC capability to cancel high interference level already in the channel equalization stage. However, when the SINR is high and the interference level is low, we observe that the performance of OMP-IC and OMP-NoIC are comparable. This is because, the noise induced by low interference may be lower than the noise floor leading to inefficiency of interference rejection. For this reason, our scheme includes the switching mechanism to block IC operations at high SINR values. A similar gain is observed in Fig. 5(b), where we fix the SINR to 0 dB. Here, interestingly the results do not change much as we increase the length of the training sequence. This result emphasizes that the true limitation on the performance of the channel estimation is the interference level.

An interesting performance exploration is the decoder’s behavior for the practical case where the two signals do not collide perfectly. In this case, if the time of the interference-
free channel is identified well, a valid approach would operate PIC/OMP-IC at times when interference exists, and use NoIC/OMP-NoIC when the channel is interference-free, which emphasizes the need for our switching mechanism. Adopting this approach, Fig. 6 shows the output SNR in the case where only signals from the fixed node arrive at the first 4 s of reception; collision occurs between time 4 s and 11.5 s; and then only signals from the mobile node exist after 11.5 s. In this scenario, we consider the transmitters to be 1000 m and 1100 m from the receiver.

Fig. 6(a) and Fig. 6(b) show the results for the far and near sources, respectively. We observe that when a collision occurs, the output SNR obtained by the NoIC/OMP-IC and the NoIC/OMP-NoIC drops significantly both for the jamming (near) source and the jammed (far) source. However, for our PIC/OMP-NoIC, we observe that a gain increases of 8 dB and 6.5 dB output SNR for the far and near sources respectively, compared to the NoIC/OMP-NoIC. When we use IC for both channel estimation and channel equalization (PIC/OMP-IC), an even more significant gain of 12 dB and 11 dB output SNR is observed. We thus claim a gain of 4 dB and 5.5 dB for channel estimation with IC for the far and near sources, respectively. Still, the effect is not obvious, since results of the NoIC/OMP-NoIC are roughly the same as the NoIC/OMP-IC. When the interference is high enough, the decoding fails and the error propagates back to the channel estimation, so the communication performance will degrade. Combining IC for both channel estimation and channel equalization solves this matter.

Next, we investigate the relationship between the range and the output SNR. The range versus the output SNR is shown in Fig. 7 for a stationary node located 1000 m from the receiver and for the mobile node located from 100 m to 2000 m to the receiver. Here, we only consider perfect alignment between the received signals. The results are explored as a function of the ratio $d_m/d_f$ (distance ratio), where $d_m$ and $d_f$ denote the distances between mobile node and the fixed node to the receiver respectively. Observing Fig. 7(a) and Fig. 7(b), we conclude that when the mobile node is closer to the receiver (i.e., the distance ratio is smaller than 1), the output SNR of the signals received from the mobile node is higher since it experiences less interference. When the distance ratio is greater than 1, the opposite result occurs. As expected, the NoIC receivers (both for the NoIC/OMP-IC and NoIC/OMP-NoIC) obtains the lowest output SNR since the interference is not mitigated at channel equalization. For example, compared the NoIC/OMP-NoIC with our PIC/OMP-NoIC, we observe that the latter obtains higher output SNR by roughly 5-8 dB. We also observe that when the distance ratio is between 0.6 to 1.6, the gain obtained by the PIC/OMP-IC is high, while when the distance ratio is less than 0.6 or greater than 1.6, the gain drops. This is because, in the presence of very high interference, the IC capability drops. Further, observing the output SNR obtained by the SIC/OMP-NoIC benchmark, it can be seen that while results improve comparing to the NoIC/OMP-NoIC, but the output SNR obtained by SIC/OMP-NoIC is still lower than that obtained by our PIC/OMP-IC.

Next, we investigate performance under different SINRs to determine the threshold level $\theta$ which is used for operating the switching mechanism. We consider the transmitters to be 1000 m and 500 m, and use the estimated channels to measure the filter coefficients. Fig. 8(a) shows the SINR versus the output SNR for the far node. We observe a monotonous increase of the output SNR obtained by the NoIC/OMP-IC and NoIC/OMP-NoIC in Fig. 8(a), while the output SNR obtained by the PIC/OMC-NoIC and PIC/OMP-IC converges for $\rho_{x1} > 6 \text{ dB}$. In this case, the dominating factor is the channel estimation accuracy rather than the interference in the DFE branch. Another way to determine the threshold is through the channel characteristics. In Fig. 8(b), we show the...
relationship between SDF in (31) and SINR in (2). We observe that the output SNR obtained by the PIC/OMP-NoIC is lower than that of the NoIC/OMP-NoIC when $\rho_{T_1 \geq 8\text{ dB}}$. From Fig. 8(b), it can be obtained TH=3.1 when $\rho_{T_1 \geq 8} = 8$.

**B. Sea experiment**

1) **Experimental Setup:** In our solution to the near-far problem, we assume the channels’ taps of the near and far links are not correlated. In this way, we could separate the IC operation for both signals. In fact, because of different channel fading and time-varying for underwater acoustic channels, the assumption is always satisfied. To demonstrate the performance over a real sea environment and to show the applicability of our approach, we conducted a designated sea experiment across the shores of Haifa, Israel in July 2019. The experiment included a deploying vessel that served as the far source; a buoy controlled from shore via an extended WIFI link that was assigned as the near source; and a submerged buoy holding an array of 7 hydrophones with matching recorders, which served as the receiver. The two transmitters were deployed at a depth of roughly 5 m, while the receiving array was deployed at a depth between 3 m and 10 m with equally-spaced hydrophones. The depth of the test field was around 12 m, the sea was calm with 0.5 m waves, and the sound speed was measured 1530 m/s throughout the water column. A diagram of the experiment’s deployment setup, and a picture taken underwater of the array is shown in Fig. 9(b).

We tested several distances between the far node and the receiving array: $d_1 = 700\text{ m}$, $d_3 = 1040\text{ m}$, and $d_3 = 1554\text{ m}$, while the distance between the anchored buoy (near node) and the array was fixed at 530 m. That is, the signal from the buoy was always stronger than that from the boat. The signals emitted were at frequency range of 7 kHz to 17 kHz, the transmitters were software defined modems of EvoLogics Inc., and the receivers were self made acoustic recorders. Table I summarizes the parameters for the tested signals. The lengths of feedforward filter, feedback filter, and IC filter were 300 symbols, 149 symbols, and 149 symbols, respectively, and the length of the training sequence was 144 ms. Fig. 10 shows an example of channel impulse response recorded for the near and far sources. We observe that the time delay is quite short (less than 10 ms). Yet, the channels clearly exhibit time-varying characteristics.

**Fig. 9:** The deployment diagram. (a) The experiment diagram. (b) The experiment deployment.

**Fig. 10:** The channel impulse responses. (a) The channel impulse response from Tx1 to Rx3. (b) The channel impulse response from Tx2 to Rx3.

Figure 11 shows the correlation coefficient between the channel impulse responses from Tx1 to Rx3 and from Tx2 to Rx3. While we observe time variation for the correlation coefficient, the maximum coefficient remains below 0.4. This demonstrates that the structure of the two channels is different as expected from the spatially dependent underwater acoustic channel. In Table II, we show the measured spatial diversity factor ratio $SDFR_{Tx1}$ and the SINR for the strong signal $\rho_S$. From the table, we observe that the distance ratio $d_1/d_2$ decreases with the metrics $SDFR_{Tx1}$ and $\rho_{T_1 \geq 8}$. This reflects the level of the far signal is not negligible compared to that of the near signal.

**TABLE I: Parameter settings in sea trial**

| Parameters | Description          | Value |
|------------|----------------------|-------|
| $R_T$      | Symbol rate          | 3125 symbol/s |
| $N_T$      | Number of transducers| 2     |
| $N_R$      | Number of hydrophone channels | 7     |
| $K_{os}$   | Over sampling factor | 1     |
| $T_{ch}$   | Channel impulse response duration | 48 ms |
| $L$        | Length of discrete channel | $L = T_{ch} \times R$ |
| $N_{ff}$   | Feedforward filter span | 2$L$ |
| $N_{ff}$   | Feedback filter span  | $L - 1$ |
| $N_{ic}$   | Interference cancellation filter span | $L - 1$ |

**TABLE II: SDF and SINR**

| Distance | $\kappa_S/\kappa_W$ | SINR (dB) |
|----------|---------------------|-----------|
| 700 m    | 1.97                | 3.25      |
| 1040 m   | 2.37                | 4.52      |
| 1554 m   | 6.13                | 8.82      |

2) **Sea trial Results:** Fig. 12 shows the output SNR when $d_1 = 700\text{ m}$. According to Table II, in this case $\kappa_S/\kappa_W = 1.97$, which will activate the IC of both the weak and the strong branches. In the first 2.1 s, the near node transmits, while...
In this paper, we considered the near-far problem in the setting of an Internet of Underwater Things (IoUT) sensor network, where nodes are non-synchronized and deployed in a mesh network such that a packet from a near source jams that of a far source. In contrast to common approaches that first decodes the strong signal and ignores the weak signal, our approach design to decode the weak and strong signal in parallel. The IC is performed both for channel estimation and for channel equalization. This approach produces better output SNR results and thus holds the benefits of lower latency factor ratio in Table II is high and so is the SINR for the near source. In this case, it is very hard to estimate the channel from the far node, and the IC switch for decoding the strong source opens (inactive), while the switch for the weak source closes. The benefit of this operation is demonstrated in Fig. 14(b), where we observe that all methods obtain similar performance for decoding the near signal, but the PIC/OMP-IC achieves a gain of more than 1 dB for decoding the far signal. The average output SNR for the corrupted signal is shown in Table III.

V. Conclusion

The output SNR for the corrupted signal is shown in Table III.
TABLE III: Average output SNR for corrupted signals

| PIC/OMP-IC     | PIC/OMP-NoIC | SIC/OMP-NoIC | NoIC/OMP-IC | NoIC/OMP-NoIC |
|----------------|--------------|--------------|-------------|---------------|
| The far transmitter located at 700 m |               |              |             |               |
| Far Node (dB)  | 8.96         | 6.58         | 5.65        | 5.00          | 4.94          |
| Near Node (dB) | 13.92        | 10.15        | 9.79        | 9.57          | 9.79          |
| The far transmitter located at 1040 m |               |              |             |               |
| Far Node (dB)  | 9.18         | 6.50         | 5.83        | 5.06          | 4.71          |
| Near Node (dB) | 15.38        | 12.18        | 11.89       | 11.82         | 11.89         |
| The far transmitter located at 1554 m |               |              |             |               |
| Far Node (dB)  | 2.31         | 1.87         | 1.78        | 1.77          | 1.77          |
| Near Node (dB) | 16.33        | 16.12        | 16.12       | 16.03         | 16.12         |

that, when channel estimation is accurate, results will always improve compared to the successive IC approach. Considering the case of very low or very high SINRs where the interference cancellation will fail or may distort the reception, respectively, we proposed a switching mechanism that controlled the IC operation. As we showed in numerical simulations and demonstrated in a designated sea trial, a significant higher output SNR was obtained for both the far and near signals, leading to a more stable IoUT network.

ACKNOWLEDGMENT

The authors would like to thank Shlomi Dahan, Liav Nagar, Ilan Shahar, Talmon Alexandri, and Dror Kipnis for their help with conducting the sea trial.

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