A novel signal detection algorithm of multiple-input multiple-output Vertical-Bell Laboratories Layered Space-Time for underwater acoustic networks based on the improved minimum mean square error

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Abstract
Multiple-input multiple-output is a commonly used technology supporting for high-rate transmission over frequency-selective fading channels with multiple antennas. Vertical-Bell Laboratories Layered Space-Time is a detection method of a multiple-input multiple-output system, which establishes a direct correspondence between antennas and layers. Studies demonstrate that multiple-input multiple-output Vertical-Bell Laboratories Layered Space-Time is a meaningful way for underwater acoustic networks of high performance. However, considering the hardware constraints and energy consumption, achieving a trade-off between the bit error ratio and complexity is a crucial issue for underwater acoustic networks of multiple-input multiple-output Vertical-Bell Laboratories Layered Space-Time systems. This article proposes a novel signal detection algorithm of multiple-input multiple-output Vertical-Bell Laboratories Layered Space-Time. First, we address the unitary matrix of the underwater acoustic channel by LDLH decomposition. Second, we order the detection sequence based on the permutation matrix. Third, we detail the implementation of interference cancelation and slice processing. Finally, we perform experiments for comparing the bit error ratio, energy consumption, processing delay, and complexity of the proposed algorithm with zero-forcing Vertical-Bell Laboratories Layered Space-Time, minimum mean square error Vertical-Bell Laboratories Layered Space-Time, and maximum likelihood Vertical-Bell Laboratories Layered Space-Time. Results indicate that our algorithm maintains bit error ratio and the processing delay to that of maximum likelihood Vertical-Bell Laboratories Layered Space-Time algorithm. However, it reduces the energy consumption, which achieves a good trade-off between performance and complexity. This work supports on constructing underwater acoustic networks of multiple-input multiple-output Vertical-Bell Laboratories Layered Space-Time system.

Keywords
Multiple-input multiple-output Vertical-Bell Laboratories Layered Space-Time, underwater acoustic networks, bit error ratio, complexity, LDLH decomposition

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Introduction
Underwater acoustic networks (UANs) have a wide range of application scenarios, such as marine data
collection, environmental monitoring, resource survey, earthquake and tsunami monitoring, auxiliary navigation, ocean robots, and autonomous underwater vehicle (AUV) control. Comparing with terrestrial networks, an UAN has some defects, such as high path attenuation, severe multipath effects, Doppler diffusion, limited bandwidth, and fast time-varying channel. In addition, the characteristic of the underwater acoustic (UWA) channel is usually considered, for example, scattering, reflection, and delay. The multipath propagation of UWA channels is large, resulting in severe inter-symbol interference (ISI), which influences the received signal quality and requires channel equalization for compensation.

Multiple-input multiple-output (MIMO) is a technology for multiplexing based on multiple transmission and receiving antennas in space. Studies demonstrate that it provides multiplexing gain and diversity gain. An MIMO system based on space–time coding suppresses the influence of fading to obtain higher channel capacity and improves the quality of the UAN greatly. It is a solution to realize the high-performance communication based on layered space–time codes (STCs), which has a good potential for improving the spectrum utilization. Vertical-Bell Laboratories Layered Space-Time (V-BLAST) is a detection method of an MIMO system, which establishes a direct correspondence between antennas and layers. In an MIMO V-BLAST system, the \(i\)th data stream is directly sent to the \(i\)th antenna after encoding, and the correspondence does not vary periodically. The data stream is an ongoing vertical column vector in the time and space domain. Therefore, in the detection procedure, as long as we know which antenna the data are sent, we can determine the layer it belongs to.

Generally, linear detection methods such as zero-forcing (ZF), minimum mean square error (MMSE), or non-linear ones, for example, maximum likelihood (ML) or sphere decoder (SD) are adopted in MIMO V-BLAST systems. Experiments show that linear methods have low complexity. However, in the time-varying UWA channel, the bit error ratio (BER) is extremely high, and the performance cannot be guaranteed. Although non-linear algorithms maintain a better performance, their complexity is high, which increases the design difficulty and the manufacturing cost.

In addition, the high complexity will lead to the rapid energy exhaustion of nodes. As we know, nodes are powered by batteries, and it will shorten the survival time of UANs. Consequently, in MIMO V-BLAST systems, it is a hot topic for designing a detection algorithm based on the trade-off between performance and complexity.

This article proposes a signal detection algorithm of an MIMO V-BLAST system based on improved MMSE. The main contributions of this article list as follows: first, we design a method for resolving the unitary matrix \(Q\) of the UWA channel based on LDL decomposition; second, we use the permutation matrix to sort the detection sequence; third, we implement the interference elimination and slice processing; and finally, we perform experiments for comparing the BER, energy consumption, processing delay, and complexity of the proposed algorithm with ZF V-BLAST, MMSE V-BLAST, and ML V-BLAST. The experimental results show that our algorithm maintains the BER and the processing delay, which are equivalent to that of ML V-BLAST. However, it reduces the energy consumption and complexity, which achieves a good trade-off between performance and complexity.

The remainder of this article is organized as follows: section “Related work” provides an overview of the related work. Section “The signal detection algorithm based on improved MMSE” describes the proposed signal detection algorithm. The simulation is discussed in section “Simulation and results.” Finally, section “Conclusion” concludes this article.

### Related work

At present, significant progress has been made in signal detection of underwater MIMO V-BLAST systems. Y Jiang and X Bai propose a BLAST-based UAN, in which V-BLAST encoding is utilized in the transmitter. The simulation proves that it overcomes multipath interference effectively and achieves a significant increase in data transmission rate. Q He et al. present an MMSE-based iterative equalization method for UANs. In the algorithm, the UWA channel is split into sub-channels for constructing a multiple-input, multiple-output orthogonal frequency-division multiplexing (MIMO-OFDM) system. MMSE equalization is applied to the inter-channel interference (ICI). Simulation results demonstrate that the performance is improved.

KS Vishvakshan et al. propose a multi-carrier system for UANs, in which dual space–time transmission diversity (DSTTD) is implemented at the transmitter end, and the fast Fourier transform (FFT) at the receiver end. Simulation illustrates that it provides a better BER by reducing the effect of the channel interference and acoustic noise while having a lower signal-to-noise ratio (SNR). Z Yang and Y Zheng design a signal detector for a UWA MIMO system, which uses the improved proportional normalized least mean square (IPNLMS) algorithm for channel estimation. Simulation demonstrates that the BER is improved.

I Nelson et al. investigate the performance of an underwater MIMO-OFDM system based on turbo codes (TCs), which regard the TC as a channel encoder and implement a non-linear detector based on ZF.
Simulation shows that it provides an achievable BER with a lower SNR. Y Zhang et al.\textsuperscript{14} propose a channel estimation scheme for underwater MIMO communication based on the soft decision. Experimental results indicate that the channel estimation has greater improvement in performance. J Han et al.\textsuperscript{15} propose low-complexity per-vector and block equalization algorithms of MIMO orthogonal signal division multiplexing (OSDM) for time-invariant and time-varying channels, respectively. Simulation results demonstrate that these algorithms have only a linear complexity in the transformed domain. MT Altabbaa\textsuperscript{16} designs a channel estimation algorithm for UWA channels undergoing Rayleigh fading with impulsive noise. The simulation shows that the proposed approach outperforms the compressed sensing-based matching pursuit (MP) algorithm and the projected matching pursuit (PMP), and the basis pursuit-based generalized approximate message passing (GAMP) algorithm.

S Zhao et al.\textsuperscript{17} propose an adaptive turbo equalizer for differential OFDM systems in UWA communications. Experimental results demonstrate that it outperforms the MMSE-based turbo equalizer for coherent systems in medium-to-high SNR region, while reducing complexity. X Zhang et al.\textsuperscript{18} propose a delay-based detection algorithm for layered space–time signals of UWA communications. Experiments show that it achieves a performance gain up to 4 dB for a UAN of $2 \times 2$ MIMO. BL Thanh et al.\textsuperscript{19} propose a method that combines MMSE and interference cancelation to suppress the ICI of UWA channels in an MIMO-OFDM system. In the algorithm, the received signal is separated into several groups, which are detected in successive iterations. Experiments show that it has a significant improvement in BER.

F Jiang et al.\textsuperscript{20} present a block Gauss–Seidel method for large array signal detection in UANs. Results demonstrate that the proposed scheme achieves almost the same performance compared to original Gauss–Seidel method, but with less processing delay. T Ebihara et al.\textsuperscript{21} present a UWA communication scheme by combining the Doppler-resilient orthogonal signal division multiplexing (D-OSDM) and MIMO signaling. The simulation results show that MIMO D-OSDM achieves better BER than the benchmarks.

In summary, there are some studies focus on the signal detection in UANs. They verify the feasibility of MIMO V-BLAST from different perspectives. However, most of the studies are difficult to achieve a compromise between performance and complexity. Therefore, there are still considerable gaps in the actual applications of MIMO V-BLAST for UANs.

The signal detection algorithm based on improved MMSE

Modeling of the underwater MIMO V-BLAST system

In this article, we model an underwater MIMO V-BLAST with $M$ transmitting antennas and $N$ receiving ones. Because V-BLAST is the spatial multiplexing of an MIMO system, to improve the spectral efficiency, the transmission signal is not encoded. Therefore, the receiving end just has a unique solution in case of $N \geq M$. The framework of an underwater MIMO V-BLAST system is illustrated in Figure 1.

In the system, the data stream is split into $M$ sub-streams via the de-multiplexer at the transmitting end, and each one is transmitted after being converted into a symbol by a modulator. Antennas at the receiving end will receive symbols. The signal vector is received by the V-BLAST receiver and is able to be resolved and converted into $M$ sub-streams via the demodulator. At the same time, sub-streams are transformed into data streams through a multiplexer.

To resolve the independent signal at the transmitting end, we assume that the UWA channel as a Rayleigh fading one in a rich scattering environment.\textsuperscript{22} Given that in an underwater MIMO V-BLAST system, the received signal vector can be expressed as equation (1)

\[
Y_N[k] = H_{NM}X_M[k] + N_N[k] \tag{1}
\]

where equation (1) is converted into matrix form, as shown in equation (2)
\[
\begin{bmatrix}
Y_1[k] \\
Y_2[k] \\
\vdots \\
Y_N[k]
\end{bmatrix} = \begin{bmatrix}
h_{11} & h_{12} & \ldots & h_{1M} \\
h_{21} & h_{22} & \ldots & h_{2M} \\
\vdots & \vdots & \ddots & \vdots \\
h_{N1} & h_{N2} & \ldots & h_{NM}
\end{bmatrix} \begin{bmatrix}
X_1[k] \\
X_2[k] \\
\vdots \\
X_M[k]
\end{bmatrix} + \begin{bmatrix}
N_1[k] \\
N_2[k] \\
\vdots \\
N_N[k]
\end{bmatrix}
\]  

(2)

In equation (2), \(Y_N[k]\) means the received signal vector of \(N \times 1\) dimensions and \(X_M[k]\) means the transmitting signal vector of \(M \times 1\) dimensions. \(H_{NM}\) is the channel matrix of \(N \times M\) dimensions, and \(h_{ji}\) is the transfer function from the \(i\)th transmitting antenna to the \(j\)th receiving antenna. \(N_N[k]\) represents a complex Gaussian noise channel, the covariance matrix is \(\sigma^2 I_N\), and \(k\) is the time index.

Frame is the data unit of a V-BLAST system;\(^2\) the structure of which includes a training sequence of the time index. The length of a frame is \(K_T\) and a payload of length \(K_P\). Therefore, the length of a frame is \(K = K_T + K_P\). The training sequence places on the front of a frame, which is used to estimate the channel matrix and the noise variance. The payload is subsequent to the training sequence and is designed for transmitting data. For simplicity, the time index \(k\) is omitted; therefore, \(Y_N\) is expressed as

\[
Y_N = H_{NM}X_M + N
\]

(3)

We consider that each receiving antenna has the same noise power, and the channel coefficient is 1. Thus, the average SNR received in an MIMO V-BLAST system is

\[
\rho = \frac{1}{N} \sum_{n=1}^{N} \text{SNR}_n = \frac{M}{\sigma^2}
\]

(4)

The detection procedure of an MIMO V-BLAST system

In the detection procedure of an MIMO V-BLAST system, only the signal of a transmitting antenna is stripped in a round. The detection algorithm will be executed iteratively until all signals are detected. Therefore, the detection sequence will affect the performance of the algorithm. The detection procedure of an MIMO V-BLAST system is shown as follows:

Step 1: estimating the UWA channel information which includes the channel matrix and the noise covariance.

Step 2: determining an optimal detection order, that is, \(S = \{p_1, p_2, \ldots, p_m\}\) and the corresponding ZF vector set, which is \(\{g_{p_1}, g_{p_2}, \ldots, g_{p_m}\}\).

Step 3: sampling signal vectors and implementing the signal detection based on the ZF vector set, as shown in equation (5)

\[
y_m = g_{p_m}x_m
\]

(5)

where \(y_m\) represents the signal of the \(m\)th transmitting antenna.

Step 4: slicing the signal \(y_m\) to solve \(\Sigma_m\), as shown in equation (6)

\[
\Sigma_m = \text{slice}(y_m)
\]

(6)

Step 5: assuming \(\Sigma_m = S_m\) and eliminating the interference of \(\Sigma_m\) on the received vector, as shown in equation (7)

\[
x_{m-1} = x_m - \Sigma_m h_{p_{M-m+1}}
\]

(7)

where \(h_{p_{M-m+1}}\) represents the column \(p_{M-m+1}\) of \(H_M\). In the detection algorithm, we estimate the channel information in Step 1. Therefore, Step 2 is the core procedure, which is to determine an optimal detection order. Then, in Step 3, we sample the signal vector and implement the signal detection based on the ZF vector set. Since it adopts frames as transmission units in the MIMO V-BLAST system, the payload processing part has exact the same sequence to dispose samples of the signal vector. Consequently, handling the optimal detection order is the main work and the most complicated part of the algorithm.

A detection algorithm based on improved MMSE

In this article, a detection algorithm based on improved MMSE is proposed. It mainly includes the LDL\(^H\) decomposition for solving the channel unitary matrix \(Q\), the detection ordering based on matrix permutation, and interference cancelation and slicing processing.

The LDL\(^H\) decomposition for solving the UWA channel unitary matrix \(Q\). In this stage, we first set the UWA channel as a global channel matrix \(H\) in \(N_R \times N_T\) dimensions, and solve the pseudo-inverse matrix \(H\). After that, \(H\) is decomposed into a positive triangle according to the data block and the equivalent channel matrix is deduced. Finally, the matrix is set to Hermitian type, and the unitary matrix \(Q\) is obtained.

The signal decomposition is the primary work. The objective function of MMSE is to minimize the mean square error (MSE) between the transmitted signal vector \(x\) and the linear combination of the received signal vector \(H^Hy\), as shown in equation (8)

\[
\arg \min_H E\left\{||x - H^Hy||^2\right\}
\]

(8)

where \(H\) is a linear combination coefficient matrix of \(N_R \times N_T\) dimensions. The optimal solution of the
channel pseudo-inverse matrix can be obtained, as shown in equation (9)

$$H = (H^H H + \sigma^2 I_{N_T})^{-1} H^H$$

(9)

where $I_{N_T}$ is the identity matrix of $N_R \times N_T$ dimensions. Thus, the estimation of the transmitted signal is generated, as shown in equation (10)

$$x = Hy$$

(10)

To simplification, we suppose that

$$R \triangleq H^H H + \sigma^2 I_{N_T}$$

(11)

Then, we get that

$$Q \triangleq R^{-1}$$

(12)

Therefore, $H$ can be expressed as

$$H = R^{-1} H^H = Q H^H$$

(13)

Since $R$ is a Hermitian matrix of positive definite in equation (11), and the inverse matrix $Q$ can be solved by the LDL$^H$ or Cholesky decomposition. Because the LDL$^H$ decomposition does not require the root operation; therefore, the complexity is less than that of the Cholesky method. In this article, we use LDL$^H$ decomposition, as shown in equation (14)

$$R = LDL^H$$

(14)

where $L$ is a lower triangular matrix of $N_R \times N_T$ dimensions, and $D$ is the diagonal matrix of $N_R \times N_T$ dimensions.

Let $R_{ij}$, $L_{ij}$, and $D_{ij}$ denote the $ij$th element of $R$, $L$, and $D$, respectively. The LDL$^H$ decomposition is performed, as shown in equation (15)

$$D_{ij} = R_{ij} - \sum_{k=1}^{i-1} L_{ik} D_{kj}$$

(15)

$$L_{ij} = \left( \frac{D_{ij}}{D_{ji}} \right)^*$$

Therefore, the inverse matrix $Q$ of $R$ is expressed in equation (16)

$$Q = R^{-1} = (L^{-1})^H D^{-1} L^{-1}$$

(16)

where $L^{-1}$ is a lower triangular matrix of $N_R \times N_T$ dimensions and $D^{-1}$ is the diagonal matrix of $N_R \times N_T$ dimensions. Since $D$ is a diagonal matrix, it just takes the reciprocal of the elements on the diagonal of $D$ to get $D^{-1}$. The calculation of $L^{-1}$ can be obtained by forwarding substitution, which is shown in equation (17)

$$L_{ij} = 1$$

$$T_{ij} + i = - L_{i, i}$$

(17)

where $L_{ij}$ and $T_{ij}$ represent the $ij$th element of $L$ and $L^{-1}$, respectively.

The detection sequence ranking based on the matrix permutation. In the above steps, $Q$ has been obtained based on LDL$^H$ decomposition. In this stage, we should determine the optimal detection order, that is, to locate the smallest element on the diagonal of $Q$ accordingly.

After solving $Q$, we ascertain the $k$th element as the smallest unit on the diagonal of $Q$, which is an optimal detection order. To facilitate the order reduction of $Q$, we swap the $k$th element and the $m$th one. The swapping procedure can be obtained based on the permutation matrix $A_k$. Let $Q_m$ be a matrix of $m \times m$ dimensions. After swapping, $Q_m$ can be expressed as

$$Q_m = A_k Q A_k$$

(18)

where $Q_{m-1}$ is a matrix of $(m - 1) \times (m - 1)$ dimensions, $Q_{m-1}$ is a vector of $(m - 1) \times (m - 1)$ dimensions, and $q_{m-1}$ is a scalar of $(m - 1) \times 1$ dimensions. Due to $Q_m \triangleq R_{m-1}^{-1}$, the Cholesky decomposition for $R_m$ is expressed as

$$R_m = C_m C_m^H$$

(19)

where $C_m$ is the lower triangular matrix of $m \times m$ dimensions. Therefore, $Q_m$ can be expressed as

$$Q_m = (C_m^{-1})^H C_m^{-1}$$

$$= P_m P_m^H$$

(20)

where $P_m$ is the upper triangular matrix of $m \times m$ dimensions. After substituting, $Q_m$ can be expressed as

$$Q_m = A_k P_m P_m^H A_k$$

$$= A_k P_m \Sigma (A_k P_m^H \Sigma)^H$$

$$= \begin{bmatrix} P_{m-1} & R_{m-1} \\ E_{m-1}^T & \mu_{m-1} \end{bmatrix} \begin{bmatrix} P_{m-1} & R_{m-1} \end{bmatrix}^H$$

$$= \begin{bmatrix} P_{m-1} P_{m-1}^H + R_{m-1} R_{m-1}^H & R_{m-1} \mu_{m-1} \\ \mu_{m-1}^* R_{m-1}^H \mu_{m-1} & \mu_{m-1}^* \mu_{m-1} \end{bmatrix}$$

(21)
where $P_{m-1}$ is the upper triangular matrix of $(m-1) \times (m-1)$ dimensions, $\mathbf{R}_{m-1}$ is a vector of $(m-1) \times 1$ dimensions, $\mu_{m-1}$ is a scalar, $E_{m-1}$ is a vector of $1 \times (m-1)$ dimensions, and $\Sigma$ is the unitary transformation.

Let $Q_{m-1} \triangleq Q_{m-1} + \mathbf{R}_{m-1} \mathbf{R}_{m-1}^H$, $q_{m-1} \triangleq \mathbf{R}_{m-1} \mu_{m-1}^*$, and $s_{m-1} \triangleq \mu_{m-1} \mu_{m-1}^*$, then $Q_m$ is expressed as

$$Q_m = \begin{bmatrix} Q_{m-1} & q_{m-1} \\ q_{m-1}^H & s_{m-1} \end{bmatrix}$$  \hspace{1cm} (22)

According to equation (22), the expression for solving $Q_{m-1}$ is shown as

$$Q_{m-1} = Q_{m-1} - \mathbf{R}_{m-1} \mathbf{R}_{m-1}^H$$

$$= Q_{m-1} - \frac{q_{m-1} q_{m-1}^H}{\mu_{m-1}^2}$$

$$= Q_{m-1} - \frac{q_{m-1} q_{m-1}^H}{\mu_{m-1}^2}$$  \hspace{1cm} (23)

where $\mu_{m-1} = q_{m-1} / \mu_{m-1}^*$, based on the iterative computations, the smallest element on the diagonal of $Q$ can be found. Thus, the optimal detection sequence can be determined efficiently.

**Interference cancelation and slice processing.** After the above two stages, it is necessary to perform the interference cancelation and slicing of the signal. In the payload processing part of an MIMO V-BLAST frame, according to the optimized detection sequence, the signal detection and interference cancelation are performed based on the optimal detection order for each signal sample. The ordered ZF vector is expressed as

$$g_k = \begin{bmatrix} q_{m-1}^H \\ q_{m-1} \\ \vdots \\ q_{m-1}^H \\ q_{m-1}^H \end{bmatrix} \begin{bmatrix} \mathbf{H}_m^H \mathbf{A}_k \end{bmatrix}$$

$$= \begin{bmatrix} q_{m-1}^H \\ q_{m-1}^H \end{bmatrix} \begin{bmatrix} \mathbf{H}_m^H \\ h_k^H \end{bmatrix}$$  \hspace{1cm} (24)

where $g_k$ is the column vector of $1 \times N_T$ dimensions, $[q_{m-1}^H \ q_{m-1}]$ is the $m$th row of $A_k Q_m \mathbf{A}_k$, $H_m^H$ is the matrix of $(m-1) \times N_T$ dimensions, and $h_k$ is the $k$th column of $N_R \times 1$ dimensions.

Given the output of an MIMO V-BLAST system as

$$S_m = \left( \mathbf{T}_m^H \mathbf{T}_m + \sigma^2 \mathbf{I}_m \right)^{-1} \mathbf{T}_m^H \mathbf{X}_m$$

$$= \left( \mathbf{L} \mathbf{D} \mathbf{L}^H \right)^{-1} \mathbf{T}_m^H \mathbf{X}_m$$

$$= \left( \mathbf{L}^H \right)^H \mathbf{D}^{-1} \mathbf{L}^{-1} \mathbf{T}_m^H \mathbf{X}_m$$  \hspace{1cm} (25)

In equation (25), $\mathbf{L}$ is the lower triangular matrix of $m \times m$ dimensions, $\mathbf{D}$ is the diagonal matrix of $m \times m$ dimensions, and $\mathbf{T}_m$ is the optimization detection sequence. Let $z = \frac{q^H_m \mathbf{T}_m^H \mathbf{X}_m}{\mathbf{L}^H \mathbf{D}^{-1} \mathbf{L}^{-1} \mathbf{T}_m^H \mathbf{X}_m}$, then

$$\mathbf{S}_m = \mathbf{D}^{-1} \mathbf{L}^{-1} \mathbf{T}_m^H \mathbf{X}_m$$

$$= z$$  \hspace{1cm} (26)

Supposing a detection sequence set $\{K_1, K_2, \ldots, K_m\}$ to obtain $Z$ and $\mathbf{T}_m^H$, we define an optimal sequence $\mathbf{Seq}_z$ in equation (27)

$$\mathbf{Seq}_z = [g_{K_1}^T \ g_{K_{m-1}}^T \ \cdots \ g_{K_1}^T]$$

In an MIMO V-BLAST system, as long as each column of $H_m$ is sorted according to the optimized detection order, we get $\mathbf{T}_m$, and then perform LDL$^H$ decomposition, as shown in equation (28)

$$\mathbf{H}_m^H \mathbf{H}_m + \sigma^2 \mathbf{I}_m = \mathbf{L} \mathbf{D} \mathbf{L}^H$$  \hspace{1cm} (28)

Therefore, $\mathbf{L}^H$ is deduced. Finally, the slice processing is executed, and the detected signal is shown in equation (29)

$$S_{K_m} = \text{Slice} \left( z_{K_m} - \sum_{j=1}^{m-1} S_{K_j} \mathbf{T}_m^H \mathbf{X}_m + 1, M-m+j \right)$$

The pseudo-code of the algorithm is expressed as follows:

1. opcode $1^*$
2. $Q = 0$, $R = H_0 = H$, $P = (1, 2, \ldots, m)$
   //Initialization parameter
3. for ($i = 1; i \leq m; i ++$)
4.   $K_i = \arg \min \mathbb{E} \left( |x - H_i x|^2 \right)$; //The Mean Square Error $D_k = R_i - \sum_{i=1}^{m} L_k D_k$;
5. $\mathbf{R} \leftarrow \text{Exchange}(i, K_i)$; //Exchange i and $K_i$ in $R, P$
6. $R_i = H_i \mathbf{H} + \sigma^2 \mathbf{I}_2$; //Pseudo-inverse matrix of $H$
7. $L_i = 1$; //Initialize $L$
8. opcode $1^*$ LDL$^H$ decomposition $*$
9. for ($j = i + 1; j \leq m; j ++$)
Simulation and results

In this article, we employ WOSS to build the experimental environment and perform the detection algorithm on the simulation platform which we have developed. We execute the Monte Carlo simulation based on MATLAB and compare the performance and complexity of our algorithm with ZF V-BLAST, MMSE V-BLAST, and ML V-BLAST. The main experimental parameters are listed in Table 1.

Performance comparison of the four algorithms

BER is an important indicator to verify the performance of the detection algorithm.
The BER comparison under different numbers of antennas. In this article, we set an MIMO V-BLAST system with two transmitting antennas, and the receiving antennas are 2, 4, 6, and 8, respectively. We compared the BER of our algorithm with ZF V-BLAST, MMSE V-BLAST, and ML V-BLAST. The BER under a different number of antennas is shown in Figures 2–5. It is clear that BER of the four algorithms has a downward trend as the SNR increases. As the number of antennas increases, the BER of our algorithm and ML V-BLAST decreases greatly, while that of the ZF V-BLAST and MMSE V-BLAST does not vary considerably.

Although the multi-input interference is eliminated, the noise is multiplied by the weighting matrix in ZF V-BLAST. In MMSE V-BLAST, it considers the influence of noise; therefore, the performance is superior to that of ZF V-BLAST, whether it is at a low SNR or a high one.

Our algorithm is based on improved MMSE, and we use LDL⁻¹ decomposition to resolve the optimal detection sequence. Depending on the sequence, each signal sample is checked and eliminated the interference in order. Therefore, the BER of our algorithm is close to that of ML V-BLAST.

The performance comparison in massive MIMO systems. We conduct the performance comparison for the four algorithms in massive MIMO systems. We design 16, 32, and 64 hydrophones (antennas) on the receiving end. These hydrophones are arranged in a line array and kept at a certain distance to ensure that there are no grating lobes.

To reduce energy consumption, we just give a scenario of single-user MIMO. We compare the BER of the four algorithms with increasing the receiving antennas as the SNR raises. As shown in Figure 6, with the number of antennas increases, the BER of the four
algorithms shows a downward trend. In contrast, the BER of our algorithm is slightly higher than that of ML V-BLAST.

The performance comparison under different bandwidth conditions. In an UAN with limited energy and propagation speed of acoustic signal, it is critical to compare the performance of signal detection algorithms under different bandwidth conditions.

Figure 7 shows the BER comparison of the four detection algorithms under three bandwidth conditions, which are 3, 4, and 6 kHz. It can be seen that the BER of the four algorithms has a difference in certain bandwidth conditions. As SNR increases, the BER of each algorithm has a downward trend. However, as the bandwidth increases, the BER of the four algorithms has an upward trend, and the higher the bandwidth, the higher the BER. It is clear that the BER of our algorithm is close to that of the ML V-BLAST.

As shown in Figure 7, when the SNR is less than 4 dB, the BER of four algorithms under different bandwidths is basically the same. For example, when SNR is 2 dB, the BER of ZF V-BLAST under the three bandwidth conditions approaches $10^{-1}$, and the BER of MMSE V-BLAST is slightly lower than that of ZF V-BLAST. In contrast, the BER of our algorithm approaches $10^{-2}$, and the BER of MMSE V-BLAST is close to that of our algorithm, which is already lower than $10^{-2}$. However, when the SNR is 6 dB, the BER of the four algorithms under three bandwidth conditions has a profound difference. It is clear that the BER of ZF V-BLAST is roughly $9.83 \times 10^{-2}$, when the bandwidth is 6 kHz. Nevertheless, that of ZF V-BLAST is about $1.78 \times 10^{-2}$, when the bandwidth is 3 kHz. When the SNR is 14 dB, the BER of our algorithm under the bandwidth 3 kHz is $10^{-3}$, and that of ZF V-BLAST under the bandwidth 6 kHz is $10^{-2}$. Overall, the BER of ZF V-BLAST is the highest when the bandwidth is 6 kHz, while that of our algorithm is lowest when the bandwidth is 3 kHz.

**The comparison of energy consumption of the four algorithms**

Hydroacoustic nodes usually use disposable batteries for energy supply; therefore, the energy consumption is an important indicator to measure the survival time. In UANs, the energy-saving mechanism is usually designed in the media access control (MAC) layer. The main measurement includes the total energy consumption of the network, the transmission and reception energy waste due to data conflicts. We defined an energy consumption model, which is expressed in equation (30)

$$E(i) = E_{\text{Sening}}(i) + E_{\text{MCU}}(i) + E_{\text{Transceiver}}(i)$$  \hspace{1cm} (30)$$

where $E_{\text{Sening}}(i)$ represents the energy consumption of the sensing module, and it is mainly used to obtain relevant information of the sensing object, including perception and collection of various signals. $E_{\text{MCU}}$ indicates the energy consumption of signal processing, which is mostly used for sampling, coordination, and scheduling. $E_{\text{Transceiver}}$ means the energy consumption of sending and receiving data, which is expressed in equation (31)

$$E_{\text{Transceiver}}(i) = E_{\text{Rx}}(i) + E_{\text{Tx}}(i)$$  \hspace{1cm} (31)$$
where $E_{T_x}$ means the energy consumption of transmitting signal and $E_{R_x}$ that of the receiving data. The energy consumption of the transmitting signal is related to the distance between underwater nodes and the amount of data it processed. The receiving energy consumption mainly refers to the signal detection. It can be observed that different detection strategies produce variety complexity. Therefore, the energy consumption is difference. To verify the performance of the detection algorithms, we mainly compared $E_{R_x}$, that is, the received signal energy consumption of our algorithm with ZF V-BLAST, MMSE V-BLAST, and ML V-BLAST.

In this article, the SE-MAC protocol is used in the MAC layer, which introduces a mechanism of the channel adaptive ACK, that is, the CA-ACK. According to the channel situation, the No-ACK or Imm-ACK is automatically selected and the number of ACK frames is reduced. Taking into account actual requirements, the energy consumption of acoustic devices from different manufacturers is completely different during the data transmission, reception, sleep, and idle. In this article, we set eight nodes in a single-cluster environment, and all nodes achieve one-hop communication with each other. The initial energy of each node is 2500 J. The transmitting power is 0.2 W, the receiving power is 0.15 W, the idle power is 0.07 W, and the sleep power is 0.01 W.

We compare the survival time of the four algorithms, as shown in Figure 8. It is clear that, in the 10th iteration, the residual energy of ZF V-BLAST is 15,453 J, that of MMSE V-BLAST is 13,699 J, the proposed algorithm is 12,659 J, and ML V-BLAST is 9779 J. Therefore, the energy consumption accounts for 23%, 32%, 37%, and 51% of the whole network, respectively.

The energy is exhausted, when the iteration reaches 40, 50, 71, and 79 for ML V-BLAST, our algorithm, MMSE V-BLAST, and ZF V-BLAST, respectively. It is obvious that the energy consumption of our algorithm is greater than that of MMSE V-BLAST, but lower than that of ML V-BLAST.

The experiments show that the survival time of ZF V-BLAST is relatively long. The energy consumption of the network is increased by 21% and 15% for ZF V-BLAST and MMSE V-BLAST algorithms, respectively. Compared with ML V-BLAST algorithm, the energy saving is about 37%.

The comparison of the processing delay of the four algorithms

We compare the processing delay of the four algorithms by sending packets of different sizes. Experimental results demonstrate that when the data packet is small, the processing delay of the four algorithms is basically the same, but as the packet size increases, the processing delay of the four algorithms shows an exponential increase.

As shown in Figure 9, when the packet size is less than 256 bits, the processing delay of the four algorithms is 217 ms, and that of MMSE V-BLAST and the proposed algorithm still tends to be the same, about 101.2 ms. However, the delay of ML V-BLAST is the smallest, about 78.5 ms. When the maximum size of packets is 4096 bits, the processing delay of ZF V-BLAST is 980 ms, that of the ML V-BLAST is 420 ms, and MMSE V-BLAST is 630 ms. Nevertheless, that of the proposed algorithm is just 258 ms, which means that the processing delay of our algorithm is greatly
reduced. It is due to the LDL\(^H\) decomposition method for solving the unitary matrix, which can quickly reduce dimensions of the signal matrix; therefore, the processing delay is decreased greatly.

Comparing with our algorithm, the processing delay of ZF V-BLAST has increased by 68.4\%, that of MMSE V-BLAST is 52.3\%, and ML V-BLAST is 31.6\%.

The complexity comparison of the four algorithms

The complexity of a detection algorithm directly affects the survival time of the UAN. The high complexity will lead to the rapid energy exhaustion of nodes. However, there are higher requirements on the hardware. In an MIMO V-BLAST system, the complexity is usually weighed in the computation of multipliers and adders based on the converted floating points. To quantify complexity, we define a complex multiplication as six FLOPs (floating-point operations per second) and a complex addition as two FLOPs.\(^{21}\)

In ZF V-BLAST, it needs to calculate the pseudo-inverse matrix, in which multipliers and adders are the main factors of the complexity. For an MIMO system of \(m \times n\) dimensions, the number of pseudo-inverse operations is \(n^2 \times m\) based on ZF V-BLAST. Let \(m = n\), then we simply quantify the complexity of ZF V-BLAST as \(O(n^3)\). The complexity of MMSE V-BLAST is basically the same as that of ZF V-BLAST. However, the channel noise variance must be estimated. Thus, we quantify its complexity as \(O(n^3 + 5n)\). In ML V-BLAST, it requires channel estimation, sorting, zeroing, and payload processing. Therefore, the complexity is quantified as \(O(2n^3 + 17n^2)\). Nevertheless, our algorithm is based on improved MMSE, the complexity is reflected in executing the LDL\(^H\) decomposition for solving the channel unitary matrix \(Q\), and determining the detection sequence based on the matrix permutation.

Let \(Q \in \mathbb{R}^{n \times n}\), the initial interval of is \(Q\) is \((m, n)\), and the accuracy is \(\mu\). When searching for a certain eigenvalue in \((m, n)\) based on the bisection method, the interval division needs to be performed \(N = \lfloor n(n - m/\mu) \rfloor + 1\) times. Since the endpoints \(m\) and \(n\) are included in the interval, the LDL\(^H\) decomposition is performed \(N = \lfloor n(n - m/\mu) \rfloor + 3\) times. If \(k\) eigenvalues in the interval \((m, n)\) are required, in the worst case, it is necessary to perform the segmentation operation for \(kN\) times.

When the order \(r\) of \(Q\) is large enough, a multiplication operation which requires to perform LDL\(^H\) decomposition is \(r^3/6\) times. Since LDL\(^H\) decomposition needs to be performed for each division, the number of operations required to obtain \(k\) eigenvalues is approximately \(kNn^3/6\) times. If \(n \gg m\), then the complexity of LDL\(^H\) decomposition is denoted as \(O(n^3 + 3n)\). Next, it is necessary to queue the detection sequence after the matrix is decomposed, which requires the reduction processing of \(Q\). Therefore, the complexity of the reduction process is \(O(4n)\). Followed by, it performs the signal interference cancelation, queue optimization, and slice processing. These three procedures are basically linear types, and the quantization complexity is \(O(3n)\).

All in all, the complexity of the proposed algorithm is quantified as \(O(n^3 + 10n)\). It is clear, as the number of antennas increases, the complexity of the four algorithms increases, as shown in Figure 10.

Among them, the complexity of ML V-BLAST is the highest, while that of ZF V-BLAST is the lowest. We also see that the complexity of our algorithm is slightly higher than that of MMSE V-BLAST. It is clear that the proposed algorithm reduces the complexity of ML V-BLAST, but maintains the performance of ML V-BLAST. Consequently, it achieves a trade-off between complexity and performance.

Conclusion

In this article, we propose a novel signal detection algorithm of MIMO V-BLAST system. We resolve the unitary matrix of underwater channels based on LDL\(^H\) decomposition and order the detection sequence by the permutation matrix. Followed by, we detail the implementation of interference cancelation and slice processing. Finally, we conduct experiments, which listed as follows. First, we execute the BER comparison under different number of antennas. The experiments demonstrate that, as antennas increase, the BER of our algorithm and ML V-BLAST decreases greatly, while that of ZF V-BLAST and MMSE V-BLAST does not change distinctly. Second, we conduct the BER comparison under massive MIMO systems with 16, 32, and
64 antennas, respectively. The results show that the BER of our algorithm is slightly higher than that of ML V-BLAST. Third, we carry out the comparison of energy consumption and the processing delay. The results show that the energy consumption of our algorithm is greater than that of MMSE V-BLAST, but lower than that of ML V-BLAST. And for the processing delay, it shows that our algorithm is significantly reduced. However, that of ML V-BLAST is least. Fourth, we perform the BER comparison under different bandwidth conditions. The results show that the BER of our algorithm is close to that of ML V-BLAST under the same bandwidth. Finally, we do the complexity comparison of the four algorithms. Simulation shows that our algorithm reduces the complexity of ML V-BLAST algorithm, but maintains the performance near to that of ML V-BLAST. The experiments indicate that a trade-off between performance and complexity is achieved. However, cooperative communication of UANs will be built between long distance, and the design of the underwater node based on MIMO V-BLAST is the main task we are currently working on.

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References
1. Han X, Yin J, Liu B, et al. MIMO underwater acoustic communication in shallow water with ice cover. China Ocean Eng 2019; 33(2): 237–244.
2. Yu G, Zhao D and Piao S. Target detection method using multipath information in an underwater waveguide environment. IET Radar Sonar Nav 2020; 14(2): 226–232.
3. Samala R and Deshmukh S. Doppler scaling factor estimation and receiver design for underwater acoustic communication. Wirel Pers Commun 2019; 108(4): 2415–2433.
4. Song H. An overview of underwater time-reversal communication. IEEE J Oceanic Eng 2016; 41(3): 644–655.
5. Albreem MA, Juntti M and Shahabuddin S. Massive MIMO detection techniques: a survey. IEEE Commun Surv Tut 2019; 21(4): 3109–3132.
6. Qiao G, Babar Z, Ma L., et al. Channel estimation and equalization of underwater acoustic MIMO-OFDM systems: a review. Can J Elect Comput E 2019; 42(4): 199–208.
7. Hama Y and Ochiai H. Performance analysis of matched-filter detector for MIMO spatial multiplexing over Rayleigh fading channels with imperfect channel estimation. IEEE T Commun 2019; 67(5): 3220–3233.
8. Zhao G, Wang J and Chen W. A novel signal detection algorithm for underwater MIMO-OFDM systems based on generalized MMSE. J Sensors 2019; 13(5): 1–12.
9. Jiang Y and Bai X. Research on V-BLAST based underwater MIMO high speed communication technique. Tech Acoust 2011; 30(4): 345–349.
10. He Q, Wang S and Zhang W. Low-complexity MMSE iterative equalization for multiband OFDM systems in underwater acoustic channels. In: Proceedings of the 2017 IEEE 9th international conference on communication software and networks, Guangzhou, China, 6–8 May 2017, pp.492–497. New York: IEEE.
11. Vishvaksenan KS, Nelson I, Rajendran V, et al. Performance of DSTTD-OFDM system in underwater communications. In: Proceedings of the 2015 international conference on communications and signal processing, Melmaruvathur, India, 2–4 April 2015, pp.1910-1914. New York: IEEE.
12. Yang Z and Zheng Y. Iterative channel estimation and turbo equalization for multiple-input multiple-output underwater acoustic communications. IEEE J Oceanic Eng 2016; 41(1): 232–242.
13. Nelson I, Vishvaksenan KS and Rajendra V. Performance of turbo coded MIMO-OFDM system for underwater communications. In: Proceedings of 2014 international conference on communication and signal processing, Melmaruvathur, India, 3–5 April 2014, pp.1735–1739. New York: IEEE.
14. Zhang Y, Zakharov YV and Li J. Soft-decision-driven sparse channel estimation and turbo equalization for MIMO underwater acoustic communications. IEEE J Oceanic Eng 2016; 41(1): 232–242.
15. Han J, Ma S, Wang Y, et al. Low-complexity equalization of MIMO-OSDM. IEEE T Veh Technol 2020; 69(2): 2301–2305.
16. Altabbaa MT. Double focusing: a new sparse channel estimation algorithm for doubly selective SFBC-OFDM-based underwater acoustic systems. IEEE Wirel Commun Le 2020; 9(7): 1–4.
17. Zhao S, Yan S and Xi J. Adaptive turbo equalization for differential OFDM systems in underwater acoustic communications. IEEE T Veh Technol 2020; 69(9): 1–15.
18. Zhang X, Zhang XJ and Chen S. Delay-based ordered detection for layered space-time signals of underwater acoustic communications. J Acoust Soc Am 2016; 140(4): 2714–2719.
19. Thanh BL, Makula P, Bui TT, et al. Group successive ICI cancellation for MIMO-OFDM systems in
underwater acoustic channels. In: Proceedings of the 2016 17th international conference on mechatronics-mechatronics, Prague, 7–9 December 2016, pp.1–5. New York: IEEE.

20. Jiang F, Li C, Gong Z, et al. Efficient and fast processing of large array signal detection in underwater acoustic communications. In: IEEE international conference on communications (ICC), Shanghai, China, 20–24 May 2019, pp.1–6. New York: IEEE.

21. Ebihara T, Ogasawara H and Leus G. Underwater acoustic communication using multiple-input–multiple-output Doppler-resilient orthogonal signal division multiplexing. IEEE J Oceanic Eng 2019; 44(3): 1–17.

22. Chen Z, Wang J and Zheng YR. Frequency-domain turbo equalization with iterative channel estimation for MIMO underwater acoustic communications. IEEE J Oceanic Eng 2017; 42(3): 711–721.

23. Khawla AA. Analysis of PR-V-BLAST receiver for massive MIMO under correlated channel. In: Proceedings of the 2017 international conference on electrical and computing technologies and applications, Ras Al Khaimah, United Arab Emirates, 21–23 November 2017, pp.1–4. New York: IEEE.

24. Chou C and Wu J. Low-complexity MIMO precoder design with LDLH channel decomposition. IEEE T Veh Technol 2011; 60(5): 2368–2372.

25. Yadav BK, Singh RK and Mohanty S. Performance analysis of efficient and low complexity MIMO-OFDM using STBC and V-BLAST. In: Proceedings of 2016 international conference on emerging trends in electrical electronics & sustainable energy systems, Sultanpur, India, 11–12 March 2016, pp.204–207. New York: IEEE.

26. Casari P, Tapparello C, Guerra F, et al. Open source suites for underwater networking: WOSS and DESERT underwater. IEEE Network 2014; 28(5): 38–46.

27. Wang J, Zhang S, Chen W, et al. Design and implementation of SDN-based underwater acoustic sensor networks with multi-controllers. IEEE Access 2018; 6(5): 25698–25714.

28. Lee H, Tinnirello I, Yu J, et al. A performance analysis of block ACK scheme for IEEE 802.11 networks. Comput Netw 2012; 54(14): 2468–2481.

29. Zhang M and Liu G. SE-MAC: an energy efficient MAC protocol for underwater sensor networks. Comput Technol Dev 2015; 25(3): 67–71.