RLS and LMS blind adaptive multi-user detection method and comparison in acoustic communication

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Abstract: RLS and LMS blind adaptive multi-user detection algorithm and multi-user detector was proposed to solve the problem of multi-user signal detection problem encountered in underwater acoustic communication networks. In simulation analysis, RLS and the LMS blind adaptive multi-user detector were designed and tested for synchronous and asynchronous multi-user communication process. The results of SIR comparison and MMSE comparison show that, both of the two methods can realize blind adaptive detection when any user change in multi-user communication, during this process, the training communication sequences are not needed. The RLS algorithm has about 5 dB higher in SIR compared with LMS algorithm, and the convergence velocity of RLS algorithm is also higher than LMS algorithm when the communication users change. RLS algorithm has better ability in multi-user detection than that of LMS algorithm, and it has great attraction and guiding significance for solving the problem of multiple access interference (MAI) in multi-user communication.

Key words: recursive least squares; least mean square method; multi-user detection; blind adaptive; acoustic communication

1 Introduction

In the first decades of 21th century, the countries all over the world put more efforts in ocean development, which cultivate the development of underwater acoustic communication networks[1-2] for collection and monitoring of marine information. The underwater acoustic channel is one of the most sophisticated wireless communication channel by far, its inherent characteristics of time-empty-frequency varying and narrow-band, high noise, strong multipath, long delay transmission, etc., make it difficult to meet people´s needs in a practical application using underwater acoustic communication and hydroacoustic network[3-5]. A signal processing technology with faster and farther transmitting velocity to achieve underwater acoustic communication methods and multi-user detection is urgently needed to realize accurately and effectively real-time multi-user access, improve data transmission capacity and transfer rates, and can resist external interference and improve communication efficiency and accuracy[6-8]. Code Division Multiple Access (CDMA) technology is an effective way to solve the problems above in wireless underwater acoustic communication condition[9-12]. CDMA technique allows multiple users to simultaneously share the entire band, with strong ability of anti-multipath interference and confidential, it has great attraction for development of underwater acoustic communication networks and for military usage in particular, so it has great growth prospects[13]. Since the complexity of underwater acoustic channel, when the communication condition sudden deterioration between the mobile user and the base station due to a strong interference unpredictable (appeared as new multipath environment changes, the new user interference, etc. occurs), blind adaptive multi-user detection techniques don't need to know the system parameters and don't require the user to resend the training sequence, it can make the system back to normal automatically. This characteristic for the development of underwater acoustic communication and underwater acoustic wireless communication network has great appeal and future development.

During the communication in CDMA mode in underwater environment, how to detect the user change is the most important problem. In this paper, RLS and the LMS blind adaptive detecting methods without training communication sequences are proposed to solve this problem in multi-user communication process, which can improve the speed of communication process. In order to get a quasi optimal detection method for compromise between good performance and complexity, the detecting performance of the two methods are examined and compared in simulation for synchronous and asynchronous multi-user cases.

2 RLS and LMS linear multi-user detector

2.1 LMS linear multi-user detector

Honig[14] proposed Blind Multi-user Detection Algorithm based on minimum energy output in least mean square (LMS) method, the convergence velocity is relatively slow. Poor [15] proposed Recursive Least Squares (RLS) method for faster convergence velocity, but the computational complexity increase to $O(N^2)$ (N is the spreading code length). From the angle of practicality and ease of use, LMS method is more convenient to practical application.

According to the idea of classical representation of MOE algorithm and linear multi-user detector[16-17], LMS linear multi-user detecting model should find out the minimum energy output algorithm $MOE(x_1)$ that maps on the orthogonal linear sub space of s_1, let equation $\langle s_1, x_1 \rangle = 0$ is met in each step in the derivation. On the orthogonal linear sub space of s_1, the fastest decline line is the gradient mapping of the sub space, the gradient can be decomposed into the sum of s_1 and its mapping on the orthogonal linear sub space, and the fastest decline line should decline fastest in all directions.

Define$y[i] \in L_2[0,T]$ as the waveforms been observed which is belonging to the ith time space $[iT, iT+T]$, the ith output of traditional single user matching filter is random variable:

$$Z_{MF}[i] = \langle y[i], s_1 \rangle \tag{1}$$

Similarly, the proposed definition of output of a linear transformation machine of the ith time is:

$$Z[i] = \langle y[i], s_1 + x_1[i-1] \rangle \tag{2}$$

Where, adaptive criteria of $x_1[i]$ can be derived, consider the unlimited gradient of the random variable in (3), which equal to represents the observed scalar (4).

$$MOE(x_1) = E\{\langle y, s_1 + x_1 \rangle\} \tag{3}$$

$$2\langle y, s_1 + x_1 \rangle y \tag{4}$$

Where, the section in y that is orthogonal with s_1 could be described as:

$$y - \langle y, s_1 \rangle s_1 \tag{5}$$

Thus, random progressive adaptive algorithm is:

$$x_1[i] = x_1[i-1] - uZ[i](y[i] - Z_{MF}[i]s_1) \tag{6}$$

Actually, because of the limited accuracy, the updated vector x_1 may not satisfy the orthogonal condition described in equation $\langle s_1, x_1 \rangle = 0$, so in some condition, the orthogonal mapping should be used for the substitute of $x_1[i]$. The system flow is shown in Eq.(6). It can be seen from the figure that the adaptive algorithm (6) only use the characteristic waveform and timing information of expectation user.

It does not use more information except single user matching filter, but can converge into a linear MMSE detector. Important is the ability to have the largest anti-MMSE proximity effects, while single-user detector did not. More important is that the MMSE detector has the ability with greatest effect of anti-distance, what does not exist in single user detector.

2.2 RLS blind linear multi-user detector

RLS method is actually recursive least squares algorithm. The algorithm uses an iterative approach to solve the least squares certainty canonical equations, the basic idea is that, the filter weight vector at time n-1 is known as least squares estimation $\hat{w}$-1, together with the new observational data obtained in the current time n, the filter weight vector of least squares estimation $\hat{w}$ could be calculated using an iterative method. RLS algorithm is a fast algorithm of least squares algorithm: observing the adaptive coefficient of a steady input signal input, and the adaptive coefficient of average power of the output error signal within a certain time (time average), whether the of average power reach minimum value or not could be set as the criteria for measurement of the adaptive system. RLS algorithm is a recursive least squares algorithm, it uses initial conditions known to calculate, and use the existing information included in the input new data to update the old filter parameters. The observed data length is variable.

Linear MMSE detector could be defined as $\hat{b}_1 = \operatorname{sgn}(\bar{c}_1^{\mathrm{T}} r)$, where, $\bar{c} = \frac{1}{s_1^{\mathrm{T}} R^{-1} s_1} R^{-1} s_1$.

$$R \approx E\{rr^{\mathrm{T}}\} = \sum_{k=1}^{K} A_k^2 s_k s_k^{\mathrm{T}} + \sigma_n^2 \mathrm{I} \quad (7)$$

The select weight vector $c(n)$ of index window of RLS algorithm could make the energy output which is indexed exponentially minimum.

$$\min imize \quad \sum_{i}^{n} \lambda^{n-1} \left[c^{\mathrm{T}}(n) r(i)\right]^2 \quad (8)$$

$$subject\ to \quad s^{\mathrm{T}} c(n) = 1 \quad (9)$$

Where, λ is defined as forgetting factor, satisfying $0 < \lambda < 1$. Its purpose is to make sure the data previous far away be forgotten, so it provides the ability to track non-stable environment. The answer to the question of limiting the optimization is:

$$c(n) = \frac{1}{s^{\mathrm{T}} R^{-1}(n) s} R^{-1}(n) s \quad (10)$$

$$R(n) = \sum_{i=1}^{n} \lambda^{n-1} r(i) r'(i) \quad (11)$$

The complexity of the algorithm is $O(N^2)$, the update process of $c(n)$ iteration is:

$$k(n) \approx \frac{R^{-1}(n-1) r(n)}{\lambda + r^{\mathrm{T}}(n) R^{-1}(n-1) r(n)} \quad (12)$$

$$h(n) \approx R^{-1}(n) s_1 = \frac{1}{\lambda}\left[h(n-1) - k(n) r^T(n) h(n-1)\right] \quad (13)$$

$$c(n) = \frac{1}{s_1^T h(n)} h(n) \quad (14)$$

$$R^{-1}(n) = \frac{1}{\lambda}\left[R^{-1}(n-1) - k(n) r^T(n-1) R^{-1}(n-1)\right] \quad (15)$$

2.3 Algorithm of MMSE for linear multi-user detection

The design target of minimum mean square error (MMSE) linear multi-user detector is to minimize the mean square value of estimate between user sending signal b_k and its estimate of the kth user. Selecting the wave c_1 with the length of T, that can satisfy the relation (16).

$$c_1 = \arg \min_{c_k} E\{(b_k - \langle c_k, y\rangle)^2\} \quad (16)$$

The output of decision statistic is $\hat{b}_k = \operatorname{sgn}(\langle c_k, y\rangle)$. Assume that $b = [b_1, \cdots, b_k]^{\mathrm{T}}$, and the $K \times K$ matrix $M = [m_1, \cdots m_k]^{\mathrm{T}}$ represent the linear detector of the kth user. The problem of linear detector of MMSE equals that: Find the best matrix M under the MMSE algorithm, where the cost function (17) defined by mean square error reach minimum value.

$$J(M) = E\{\| b - My \|^2\} \quad (17)$$

$$\min\{\| x \|^2\} = \min\{tr(xx^{\mathrm{T}})\} \quad (18)$$

$$\min J(M) = \min\{tr[\operatorname{cov}(b - My)]\} \quad (19)$$

Calculate the partial derivative of M in the right side of equation, and let $\frac{\mathrm{d}}{\mathrm{d}M} tr[\operatorname{cov}(b-My)] = 0$, the following equation could be defined as

$$M_{MMSE}(RA^2R + \sigma^2 I) = A \quad (20)$$

Define $G \overset{def}{=} RA^2$, and matrix A is diagonal, so $G \overset{def}{=} RA^2 = ARA$. The estimator using MMSE algorithm can be conducted by $M_{MMSE} = A\,(G + \sigma^2 I)^{-1}$, and the MMSE detector is defined as:

$$\hat{b}_k = \operatorname{sgn}[(M_{MMSE} y)_k] = \operatorname{sgn}(A_k\,([G + \sigma^2 I]^{-1} y)_k) \quad (21)$$

It can be verified, MMSE linear transformation is equivalent to the maximum of Signal to Interference Ratio (SIR) of output of linear converter can be defined as:

$$\frac{1}{\min_{c_k} E\{(b_k - \langle y, c_k\rangle)^2\}} = 1 + \max_{c_k} \frac{E\{\langle c_k, A_k b_k s_k\rangle^2\}}{E\{\langle c_k, y - A_k b_k s_k\rangle^2\}} \quad (22)$$

Select x_1 that can make $E\{(b_1 - \langle y, c_1\rangle)^2\}$ minimum, and can get:

$$E\{(b_1-\langle y,c_1\rangle)^2\} = b^2-2b_1E\{\langle y,c_1\rangle\} + E\{\langle y,c_1\rangle^2\} \quad (23)$$

Where, b^2 is independent of selection of c_1, and the data bit $b_1 \in \{-1, +1\}$, which is transmitted with equal probability, so the equation $E\{\langle y,c_1\rangle\} = E\{\hat{b}_1\} = E\{b_1\} = 0$ can be get. The minimum of $E\{(b_1-\langle y,c_1\rangle)^2\}$ equals the minimum of $E\{\langle y,c_1\rangle^2\}$, and the relation $E\{\langle y,c_1\rangle^2\} = E\{\langle y,s_1+x_1\rangle^2\}$ is just the output energy of linear detector $\langle y,c_1\rangle$. So the selection of x_1 can minimum the output energy of linear detector, that is minimum output energy algorithm.

$$MOE(x_1) = E\{\langle y,s_1+x_1\rangle\} \quad (24)$$

It can be verified, the output energy can be minimized if the selection of x_1 can minimize the mean square error, so that:

$$\begin{aligned} MMSE(x_1) &\overset{def}{=} \min E\{(A_1b_1-\langle y,s_1+x_1\rangle)^2\} \\ &= A^2 + MOE(x_1) - 2A_1^2\langle s_1,s_1+x_1\rangle \quad (25) \\ &= MOE(x_1) - A_1^2 \end{aligned}$$

where, $\langle s_1,s_1+x_1\rangle = \langle s_1,s_1\rangle + \langle s_1,x_1\rangle = 1$, because $\langle s_1,s_1\rangle = 1$ (Each user signal has a unit of energy) and $\langle s_1,x_1\rangle = 0$ (s_1 and x_1 are orthogonal).

3 Simulations and analysis

In simulation, a multi-user communication sequence model with 13 users was build up. Without loss of generality, user 1 is set to be the target user. The spreading code is a gold sequence with spreading sequence type $n = 5$ and the spreading gain is 31. The signal to noise ratio (E_b/N_0) of user1 is set as $SNR_1 = 0$ dB, user2−user6 is set to be $SNR_{2\text{-}6} = 10$ dB, user7−user12 is set to be $SNR_{7\text{-}12} = 20$ dB, user13 is set to be $SNR_{13} = 30$ dB, which means that strong MAI exist in the communication. The background is set to be affected by Gaussian white noise, the variance is $\sigma^2 = 0.01$.

3.1 RLS and LMS linear multi-user detector for synchronous multi-user detection

For synchronous multi-user detection case, blind adaptive RLS and LMS linear multi-user detector for detecting the target signal was verified. Signal access sequence of target user and interference user is shown in Fig.1, the initial signal are signal user 1-10, at the time of 600th data point, the all 13 users join in communication, and at the time of 1200th data point, there are only user2-4 remain in communication sequence, user 1 and user 5-13 are stopped. Gaussian white noise signal exists during the whole communication sequence as the analog ambient noise of underwater acoustic channel. Signal to interference noise ratio (SIR) analysis is shown in Fig.2, the effects of MMSE criteria for two detectors are analyze as is shown in Fig.3.

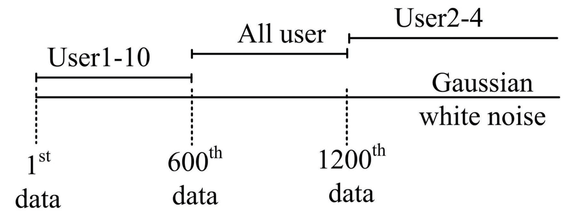

Fig. 1 Synchronous multi user signal access sequence

For synchronous multi-user detect case, RLS and LMS linear multi-user detector were used for detect the communication sequence, the comparison of signal to interference noise ratio (SIR) between the two methods are shown in Fig.2. It can be seen that RLS and LMS detector can distinguish the three intervals during the communication sequence change at the access point as is shown in Fig.1. When there is target user existing in the communication sequence, such as the interval like 1-600 and 600-1200 data point, both of the two methods can get a high SIR detect line, which means the detector can distinguish the target user from interferences, and when there is no target user, the interference signal and noise are declined to 0dB. The SIR results consistent well with access sequence of Fig.1.

The differences between RLS and LMS detector in synchronous multi-user case are that, the detect effect and convergence rate are different. Considering detect effect, when there is target user exists in communication sequence, the RLS detector can get higher SIR line than LMS detector, that can be seen in Fig.2 from 1-600 and 600-1200 data point interval. The convergence point for RLS is 5 dB higher than RLS detector, which means the more the interference user number is, the better RLS detector will have, and it will be wildly suitable for more complicated case. Considering convergence rate, when there is target user exists in communication sequence, such as 1-600 and 600-1200 data point interval in Fig.2, RLS detector can has higher convergence rate that LMS: when there is communication sequence changing, the RLS detector can converge as exponential rate during the first few data to the convergence point and then converge as linear rate to the stable state. But the LMS detector could only converge as linear rate all through the process. From these view point, RLS detector is better than LMS detector.

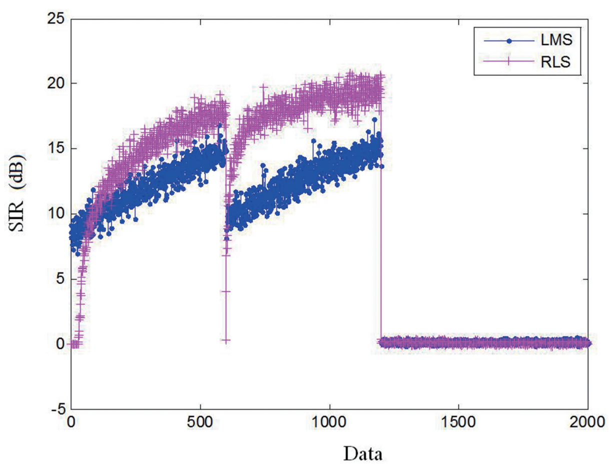

Fig. 2 SIR comparison of RLS and LMS multi-user detector for synchronous multi-user case

Since the MMSE criteriais defined as (25), the effect of multi-user detection between RLS detector and LMS detector using this criteria for comparison, as shown in Fig.3. In MMSE definition, $A_1 b_1$ is signal data for communication, and $\langle y, s_1 + x_1 \rangle$ is detector, the MMSE criteria is to approach the minimum detecting error between the estimated value and the true value of the. From the definition it can be concluded that the smaller of MMSE results, the closer to real value of the estimated results for detector is. It is obvious, as shown in Fig.3, that the RLS detector has lower detection results than LMS detector, the estimated results for RLS detector is closer to real signal. For the trends of convergence line, RLS detector and LMS detector are both sensitive to the variation of multi-user communication sequence, as seen after the point in the 600th data point, when the communication sequence changed from user1-10 to user 1-13, the detection results by MMSE criteria converged quickly after a few data points, especially for RLS detector, which converges exponentially at beginning, then gradually approaching the stable value. For comparison, the convergence velocity of LMS detector goes almost nearly for the whole process, which is obviously slower than that of RLS detector. From the comparison, it can be concluded that the RLS detector has better ability in distinguishing synchronous multi-user detection case.

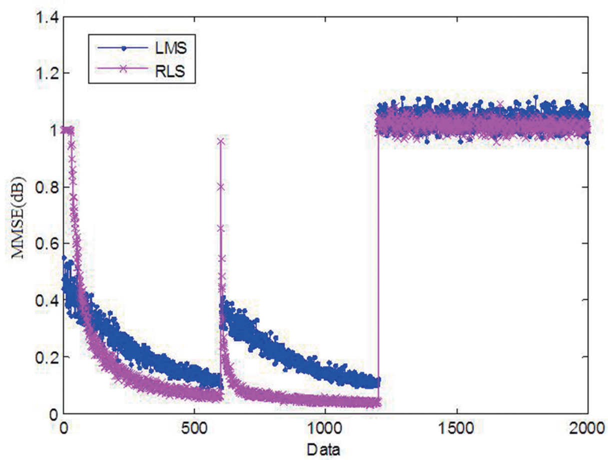

Fig. 3 MMSE comparison between RLS and LMS multi-user detector for synchronous multi-user case

3.2 RLS and LMS linear multi-user detector for asynchronous multi-user detection

For asynchronous multi-user detection case, blind adaptive RLS and LMS linear multi-user detector for detecting the target signal was verified. Signal access sequence is shown in Fig.4, the initial signal are signal user 2-5, at the time of 500th data point, the user1 joins in communication asynchronously;

and at the time of 900th data point, user 2-5 stop and user 7-13 join in the communication asynchronously. Gaussian white noise signal exists during the whole communication sequence as the analog ambient noise of underwater acoustic channel.

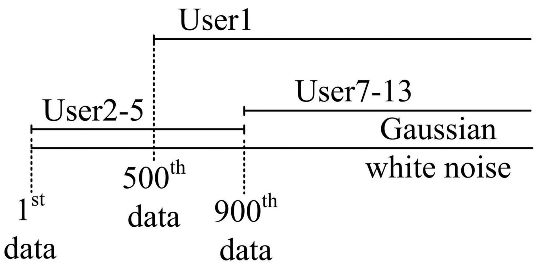

Fig. 4 Asynchronous multi user signal access sequence

For asynchronous multi-user detect case, RLS and LMS linear multi-user detector were used for detect the communication sequence, the comparison of signal to interference noise ratio (SIR) between the two methods are shown in Fig.5. It is similar with the synchronization detector that, RLS and LMS detector can distinguish the three intervals of the communication sequence change at the access point as is shown in Fig.5. When there is not target user existing in the communication sequence, as shown in interval of 1-500 data point, the SIR line for two detectors are almost 0 dB. When the target user1 access into the communication sequence asynchronously, as shown in interval of 500-900 data point, both of the two detectors can get a high SIR detect line, which means the detector can distinguish the target user from interferences user. When the user 2-5 stop and user 7-13 join in communication at time of 900th data point asynchronously, meanwhile, user 1 keep existing in communication sequence, the RLS and LMS detector re-converge back from 0dB to about 20dB. From the trends above, it can be seen that RLS and LMS detector can adaptively converge for the asynchronous changes in the communication sequence and distinguish between target user and interferences.

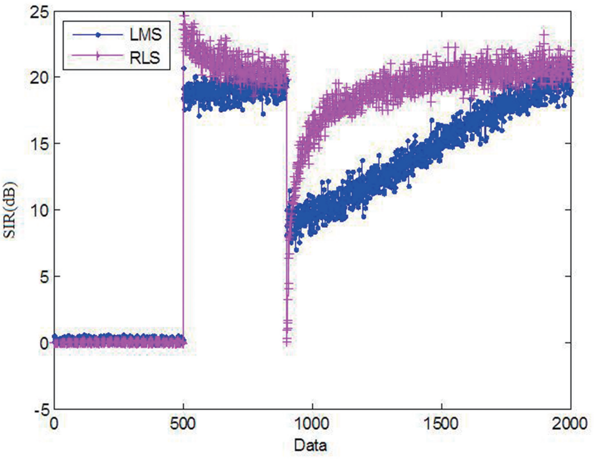

Fig. 5 SIR comparison of RLS and LMS multi-user detector for asynchronous multi-user case

The differences between RLS and LMS detector for asynchronous case are that, RLS detector has higher SIR results and convergence rate than LMS detector, which are similar to synchronous case. As shown in Fig. 5, during the interval 500-900 and 900-2000 data point, when there is target user existing, the stable convergence SIR line for RLS detector are higher than LMS detector, and the more the users are, the better the detection results are, which can be seen for the RLS line between 500-900 and 900-2000 data point compared withthe lines of LMS in Fig.5. The average increase of SIR of RLS detector can reach about 3dB compared with LMS detector.

Considering the MMSE criteria in asynchronous multi-user detection case, the results comparison between RLS and LMS detector are shown in Fig.6, the trends for detection results for the two detectors are similar with synchronous case. RLS and LMS detector both have accurate response to the change in the multi-user communication process, as shown at point of 500th and 900th in Fig.6. And when there is target user existing in the communication sequence both of the two detector can quickly reach stable state, but when there are more interference users access in communication sequence, which means the interference noise is high, RLS detector can converges at exponentially at the beginning and then approach to stable state, LMS detector has a relatively lower convergence rage as comparison. From the comparison above, in asynchronous multi-user detection case, RLS detector is superior to the LMS.

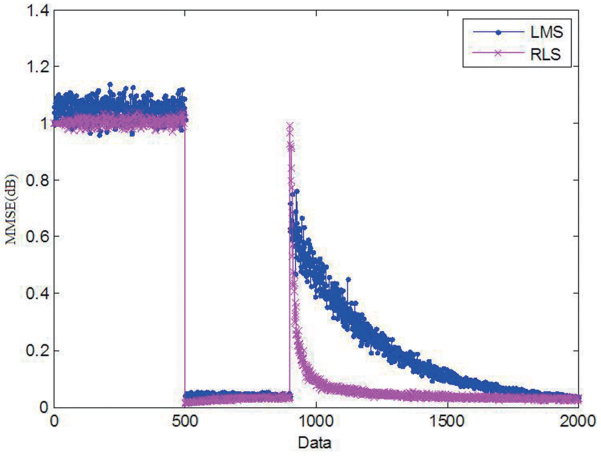

Fig. 6 MMSE comparison between RLS and LMS multi-user detector for asynchronous multi-user case

4 Conclusion

RLS blind multi-user detection algorithm is proposed in this paper and the detection characters were compared with LMS algorithm for synchronous and asynchronous multi-user case. By simulation and comparison, it can be concluded that both of the two algorithms not require training sequences and can automatically track and quickly reach convergence when user changes in communication process. RLS algorithm has higher detection results for SIR parameter, and when the communication users change, RLS has higher convergence rate than that of LMS. Considering the MMSE algorithm, the detection results of RLS algorithm are closer to real value than that of LMS algorithm. By comparison, it can be concluded that the RLS algorithm has better ability in multi-user detection than that of LMS algorithm, RLS blind multi-user detection algorithm have great attraction and guiding significance for underwater multi-user detection, it can be used to realize theaccurate and stable CDMA-based fast underwater acoustic communication protocols.

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