Artificial Fish Swarm Algorithm-Based Sparse System Estimation

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Abstract. In this paper, the estimation of Doppler-distorted underwater acoustic (UWA) channels is investigated. The UWA channels are characterized by severe multipath spread and significant Doppler effects, and can be well modeled as a multi-scale multi-lag (MSML) channel. Furthermore, exploiting the sparsity of UWA channels, MSML channel estimation can be transformed into the estimation of parameter sets (Doppler scale factor, delay, amplitude). Based on this, orthogonal matching pursuit (OMP) algorithm has been widely used. But the estimation accuracy of OMP depends on the size of the dictionary and finer resolution requires higher computational complexity. Thus, this paper proposes a new method called improved artificial fish swarm algorithm (IAFSA), for the UWA channel estimation. Different from basic AFSA, IAFSA proceeds in an iterative manner to separate multipath and will adaptively adjust fish's positions and step during each sub-iteration, thus can achieve fine resolution and fast convergence. The performance of the IAFSA is evaluated by various numerical simulations, including channels generated by BELLHOP. The simulation results show that IAFSA outperforms OMP algorithm in both estimation accuracy and computational complexity.

Keywords: Sparse system estimation · Artificial fish swarm algorithm · Underwater acoustic channel · Doppler spread

1 Introduction

Underwater acoustic (UWA) channels [1–3] pose grand challenges for reliable high data-rate communications, due to significant Doppler effects [4, 5] and severe multipath spread. In underwater communications [6–8], acoustic waves propagate at 1500 m/s, much lower than 3×10^8 m/s, the speed of electromagnetic wave in terrestrial wireless systems. Thus, the motion of platform will cause more significant Doppler effects, which is expressed as signal compressing or dilating in time domain and can be treated as Doppler scale [9]. And the multipath spread is formed by exhaustive reflections in underwater environment. For the low propagation speed of acoustic waves, multipath spread results in long time delay and severe inter-symbol interference (ISI). To fully understand the channel characteristics and overcome challenges it poses, accurate channel models and estimation methods are essential to investigate.

As observed in many experiments [10–12], signals from different paths will experience different Doppler scale, arrive at different time and have different energy, and

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the received signal will be a superposition of these signals. So the multi-scale multi-lag (MSML) channel, denoted in [13] can well model acoustic channel and has been adopted in many researches [11, 14–16]. In MSML channel model [17, 18], each path can be parameterized by Doppler scale factor, time delay and amplitude. However, for severe multipath spread, this model will be too complex to estimate. To overcome such difficulty, many researchers investigated the sparsity of UWA channel [19–21], that is, most of the energy is concentrated in some small regions. So only a few channel taps in MSML channel [22] model are nonzero and need to be tracked. As a result, the computational complexity has been reduced and many sparse channel estimation algorithms based on compressed-sensing (CS) have been proposed [11, 23–28].

These algorithms can be generally grouped in two categories: dynamic programming like matching pursuit (MP), and linear programming like basis pursuit (BP) [11, 29, 30]. BP aims at the minimization which needs high computational complexity, thus is less attractive for practical large-scale applications. Therefore, we will mainly focus on MP algorithm and its successors.

In [23], MP algorithm is applied to estimated Doppler scale factors of different paths. It iteratively selects one column from the dictionary that is most relevant with the residual signal, and subtract the estimated path component to update the residual signal. Compared with MP, it's orthogonal version, orthogonal matching pursuit (OMP) algorithm [24, 31–33] makes the residual signal be orthogonal with all the selected columns, thus has better convergence speed and accuracy. [11, 25, 26] compares the traditional subspace methods and CS-based methods for channel estimation, and concludes that CS- based methods have better performance. Meanwhile, some improved algorithms, which focus on adaptively estimating path numbers, like sparsity adaptive matching pursuit (SaMP) [27]and adaptive step size SaMP (AS-SaMP) [28] have been applied to sparse channel estimation. Furthermore, some references propose methods to reduce computation: [34, 35] proposes a two-stage OMP algorithm, which estimates the Doppler scale factor and time delay respectively, rather than simultaneously as OMP does. But it requires some preprocessing before channel estimation. [36] analyzes that fast Fourier transform (FFT) [37, 38] can be utilized in OMP to simplify calculation. But the reduction is limited as it only focuses on the computing process rather than on the reducing of column dimensions in the dictionary.

Therefore, the main limitation of MP algorithm and its successor is that the estimation accuracy depends on the size of the dictionary. To guarantee a fine resolution, the number of columns in the dictionary could be extremely large [39]. Thus, calculating inner product of received signal and each column sequentially as MP algorithm does leads to extensive calculation, especially for UWA channel, where the delay-scale spread is large. To overcome this difficulty, this paper proposes a novel algorithm called IAFSA for UWA channel estimation.

AFSA is one of the intelligent algorithms which can find the optimal solution quickly with the help of each fish's individual competition and swarm cooperation [40]. Based on AFSA, the proposed method, IAFSA, proceeds in an iterative manner and will adjust step and fish's positions during the sub-iteration. Then it will update the residual signal at the end of each iteration and return the parameters of one path. The proposed method can effectively reduce computational complexity while has a good estimation performance.

The rest of this paper is organized as follows. Section 2 gives a brief introduction of the channel model. In Sect. 3, we present the basic AFSA and the process of the proposed IAFSA in detail. Section IV focuses on the simulation results and section V concludes the paper.

2 Channel Model

UWA channel features large multipath spread for the interaction with ocean surface, bottom medium, as well as inhomogeneous particles of water column. MSML channel model can well describe the UWA multipath channel, that is:

$$h(\tau, t) = \sum_{l=1}^{L} A_l(t)\delta(\tau - (\tau_l - (a_l - 1)t)) \tag{1}$$

where L is the number of channel taps. $A_l(t)$ is the time- varying amplitude of the lth path and can be assumed to be constant during a short period of time, for example, the transmission duration of one data frame. τ_l and a_l are the time delay and Doppler scale factor of the lth path, respectively. And $\delta(\cdot)$ is a delta function defined as following:

$$\delta(t) = \begin{cases} 1 \ t = 0 \\ 0 \ otherwise \end{cases} \tag{2}$$

Let $s(t)$ be the transmitted signal and the corresponding received signal $r(t)$ can be written as:

$$r(t) = \sum_{l=1}^{L} A_l(t)s(a_l t - \tau_l) + w(t) \tag{3}$$

where $w(t)$ is the additive noise.

Given the sparsity of UWA channel, only some channel taps are nonzero in (1), which means that $r(t)$ is a superposition of only a few delay-scaled versions of $s(t)$. Therefore, the calculation complexity for channel estimation is significantly reduced.

3 IAFSA-Based Sparse Channel Estimation

3.1 Basic AFSA

AFSA (artificial fish swarm algorithm)is an optimization method which imitates the behaviors of fish, including preying, swarming and following. In underwater world, fish can find areas with higher food density based on their individual competition and swarm cooperation. Similarly, AFSA can get the optimal solution in the problem space by imitating fish behaviors. Before introducing these behaviors, we will give some definitions first.

Denoting Xp as the position of an artificial fish(AF):

$$X_p = \left(x_1^p, x_2^p, \ldots, x_N^p\right) \qquad (p = 1, \ldots, P) \tag{4}$$

where P is the population size and N is the dimension of the position.

The fitness value of position Xp can be calculated by

$$y_p = f(X_p) \tag{5}$$

And the distance between two individuals Xp and Xq is defined as

$$d(X_p, X_q) = \sqrt{\sum_{n=1}^{N} (X_p(n) - X_q(n))^2} \tag{6}$$

There are three basic behaviors of AF:

1) Preying: Suppose the current position of AF p is Xp, then it randomly selects a position Xv within its visual range. If $yv > yp$, the AF will move a step toward Xv, that is

$$X_{pnext} = X_p + \frac{X_v - X_p}{||X_v - X_p||} \cdot \Delta \tag{7}$$

where Δ is the step size. This process will repeat I times until one Xv meets the requirement, or the AF will choose a position randomly within visual.

2) Swarming: Let Xp be the current position of AF p and Q be the number of its partners within its visual range. If $Q > 0$, calculating the center position of these Q partners:

$$X_c = \frac{1}{Q} \sum_{q=1}^{Q} X_q \tag{8}$$

Define λ as the crowd factor, if $yc/Q > \lambda yp$, which means that the food density at Xc is high and the surrounding is not crowded, so AF p will move toward Xc as in (7); otherwise, it will execute the behavior of preying. If $Q = 0$, AF will also execute the behavior of preying.

3) Following: AF p finds Q partners within its visual range. If $Q > 0$, finds the partner Xq which has *the* maximum yq. Then if $yq/Q > \lambda yp$, AF p will move toward Xq as in (7). If $yq/Q \leq \lambda yp$ or $Q = 0$, AF p will execute the behavior of preying.

At each iteration, each AF calculates the fitness values of swarming and following, then selects one behavior with better fitness value. The optimal position and corresponding fitness value among all AFs will be recorded on the call-board. The algorithm will stop when reaching maximum iterations or the error meets the requirement. Then we can get the optimal solution from the call-board.

3.2 Improved AFSA (IAFSA) and Channel Parameters Estimation

Let one fish position represent one path's Doppler and delay parameters, $\{a_l, \tau_l\}_{l=1}^{L}$. And let $r(t)$ be the received signal, $s(t)$ be the preamble, then signal from path Xp can be represented as $s^{X_p}(t)$. So the fitness value can be calculated by

$$f(X_p) = \frac{\int_{-\infty}^{+\infty} r(t) s^{X_p}(t) dt}{\int_{-\infty}^{+\infty} ||s^{X_p}(t)||^2 dt} \tag{9}$$

This is just the estimated path amplitude: $f(X_p) = \hat{A}_{X_p}$. Thus AFSA can be applied to channel estimation for one-path case. However, for MSML channels, the received signal is a superposition of several different multipath components, parameter estimation is more complicated and some modifications are necessary when applying AFSA to MSML channel estimation.

Inspired by MP algorithm, we propose an improved artificial fish swarm algorithm (IAFSA) in this paper, which proceeds in an iterative manner and estimates parameters for one path at each iteration. Specifically, during one iteration, basic AFSA, with some modifications, will be applied as a sub-iteration. The modifications include step adjustment and part of fish's position adjustment. Then the estimated path component will be eliminated from the received signal by subtracting the delay-scaled version of the known preamble.

The process of IAFSA is given as Algorithm 1.

Algorithm 1: Doppler-distorted UWA channel estimation based on IAFSA

Input:

Transmitted signal vector s; received signal vector r; path numbers L; threshold ε.

Initialization:

Set the residual signal $r_e = r$, the crowd factor λ, the visual range D, the step Δ ,the number of trying I, the maximum sub-iterations k_{max}, set l=1;

Iterate:

1: Initialize a population of AF with random positions X_p $(p = 1,\cdots,P)$ in the problem space and calcu late corresponding fitness values y_p $(p = 1, \cdots, P)$. Record the maximum fitness value y_{opt} and corresponding X_{opt} on call-board.

2: Set counters $k = 1$.

3: Do swarming and following within visual range D, then select one behavior with better fitness value, and update X_p.

4: Calculate fitness value for each fish and update call- board.

5: When $k > k_{max}/2$, if call-board keeps unchanged and $y_{opt} > \varepsilon$, change half of AFs positions to be X_{opt}.

6: Set $k = k + 1$, step $\Delta' = (1 - \frac{k}{2k_{\max}})\Delta$, and loop to step 3 until $k > k_{\max}$.

7: Select the position from call-board and get the delay-scaled training signal as $\mathbf{s}_l$, and corresponding fitness value y_{opt} is $\hat{A}_l$. Then update the residual signal as:

$$r_e = r_e - \hat{A}_l s_l \tag{10}$$

8: If $l = L$, stop the iteration; else, set $l = l + 1$ and go to step 1.

Output:

The estimated channel parameters: $\{\hat{A}_i, \hat{a}_i, \hat{\tau}_i\}_{i=1}^{L}$.

Path number L can be got from the process of signal synchronization before channel estimation; and the threshold ε is set according to the energy of the signal from one path which can be detected at the receiver.

4 Experiment and Analysis

In this part, we use various computer simulations to evaluate the performance of IAFSA, and compared with OMP algorithm will also be included.

4.1 Channel 1

We consult [11]to set the path parameters in our simulation, that is, the number of discrete paths L from transmitter to receiver is 10 in total, and the inter-arrival time is distributed randomly within 25 ms with the minimal delay synchronized to zero. The path amplitudes are uniformly distributed and the strongest path is normalized to 1. The Doppler scale factors are randomly distributed within [1,1.02], with an accuracy to four decimal places. And we use a pseudo-random noise (PN) signal of 511 symbol length as the training sequence, which is binary phase-shift keying (BPSK) modulated onto the carrier. The carrier frequency is 10 kHz and the sampling rate is 20 kHz.

At the receiver, both IAFSA and OMP will be applied to channel estimation. The initialization parameters of IAFSA are listed in Table 1, while for OMP algorithm, we build a dictionary with a resolution of 1×10^{-4} in the Doppler rate and 0.1 ms in the tap delay. The dictionary covers a Doppler rate variation of 0.02 and a delay spread of 25 ms, which is also the position space of AFSA.

Table 1. Parameter of IAFSA.

Parameter	Value
Population size (P)	50
Crowd factor (λ)	0.3
Visual range (D)	[0.005;1.0 ms]
Step (Δ)	0.2
Maximum iterations ($k$max)	10
Trying number (I)	10
Threshold (ε)	0.2

Figure 1 displays the normalized mean squared error (NMSE) of the estimated scale factor versus signal to noise ratio (SNR), as defined in the following:

$$NMSE = \frac{\sum_{l=1}^{L} \left| \hat{\alpha}_l - \alpha_l \right|^2}{\sum_{l=1}^{L} |\alpha_l|^2} \tag{11}$$

From Fig. 1, it is clearly that the IAFSA outperforms OMP in Doppler scale estimating. The accuracy of OMP depends on the resolution of the columns in the dictionary, thus it is limited by the dictionary size. While IAFSA can get a better resolution by step adjusting in the sub-iteration, as well as that at the last stage of iteration, many fish will search around the optimal solution to achieve better accuracy.

The estimating error of time delay, $\frac{1}{L} \sum_{l=1}^{L} \left| \hat{\tau}_l - \tau_l \right|$ is plotted in Fig. 2. The IAFSA is slightly better than OMP in low SNR, with a gain about 2 dB. When SNR exceeds 8 dB, both algorithms become stable and IAFSA gets a lower delay estimating error, for it's search range is smaller at the last stage of sub-iteration and can get better resolution.

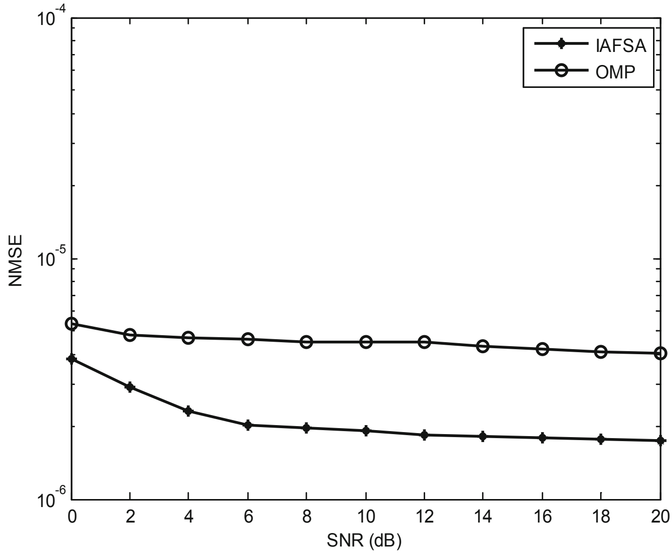

Fig. 1. NMSE of the estimating scale factor versus SNR

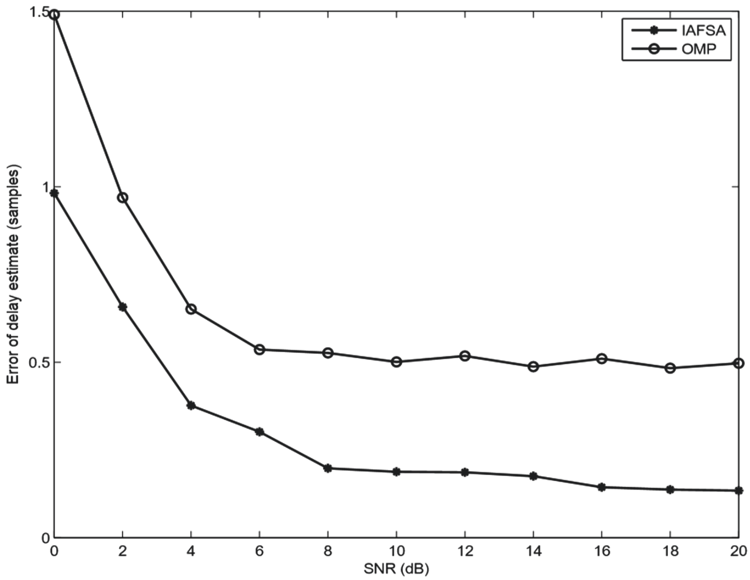

Fig. 2. Errors of the estimating delay versus SNR

Figure 3 illustrates the residual signal energy rates, $||r_e||^2/||r||^2$ versus SNR of both estimation algorithms. And a reference which uses the true channel information is also included. It can be seen that IAFSA performs better than OMP, gaining about 2 dB when SNR exceeds 2 dB and is closer to the ideal values. Residual signal energy rate is a

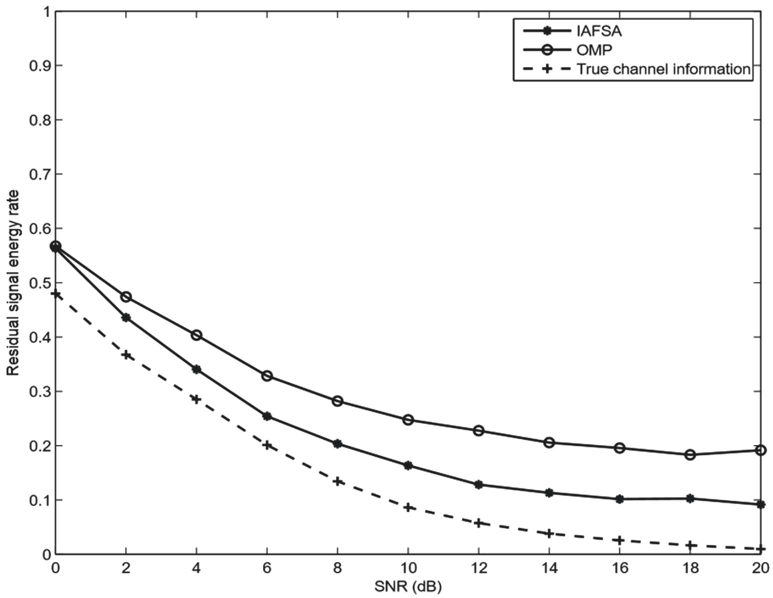

Fig. 3. Residual signal energy rate versus SNR

comprehensive evaluation of the channel estimation, that is, the estimation accuracies of Doppler scale, delay and amplitude all contribute to it. Thus, the performance in Fig. 3 is also coincident with which we analyzed in Fig. 1 and Fig. 2.

4.2 Channel 2

We use the BELLHOP beam-tracing model to mimic an underwater environment: the water is 100 m deep, the initial horizontal range between the transmitter and receiver is 2000 m. the transmitter is fixed at the depth of 80 m, and the receiver is at 50 m depth with a horizontal speed of 15 m/s toward the transmitter. The speed of the acoustic wave is set to be 1500 m/s. And the reflection coefficients of the bottom and the surface are set to 0.7 and -0.9, respectively. As shown in Fig. 4, we consider ten dominant paths and the performance comparisons are shown in Figs. 5, 6 and 7.

It is the same as in channel 1, IAFSA outperforms OMP when testing by channel 2 which is generated by BELLHOP.

In channel 2, considering the Doppler effects are mainly caused by the receiver moving. Thus, the maximum Doppler spread can be calculated as $v/c = 0.01$. And ten paths all arrive within 25 ms with the delay of the first arrival path synchronized to zero. So the difference between two channels for OMP is the column numbers in the dictionary. The dictionary size in channel 1 is twice as in channel 2 for the Doppler spread is 0.02 in channel 1. However, for IAFSA, the only adjustment is to change the position space when initializing fish positions. So it is more convenient when channel changes and does not need additional computation.

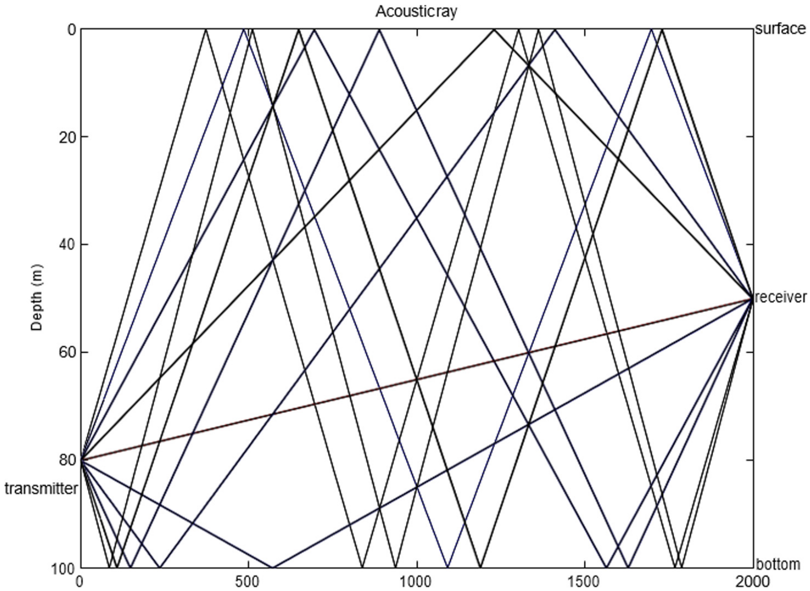

Fig. 4. Acoustic ray paths of UWA channel

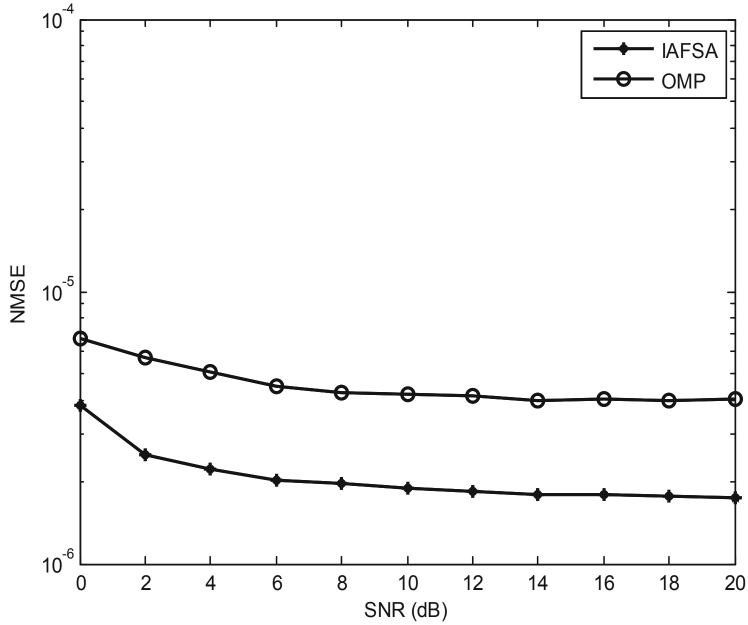

Fig. 5. NMSEs of the estimating scale factor versus SNR

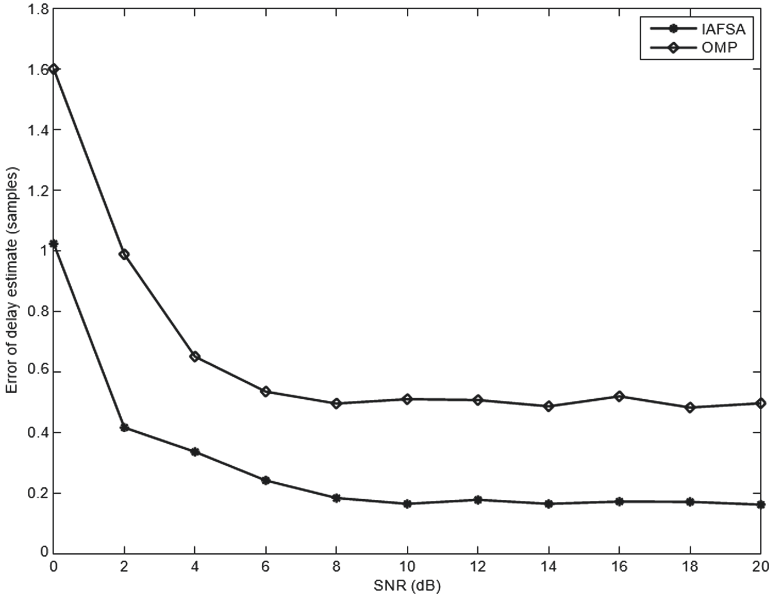

Fig. 6. Errors of the estimating delay versus SNR

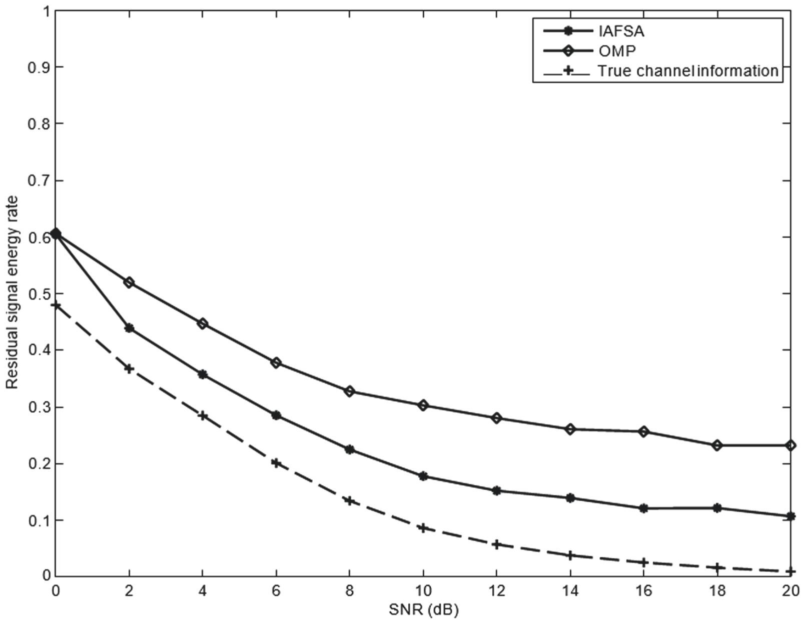

Fig. 7. Residual signal energy rate versus SNR

4.3 Complexity Analysis

As both OMP and IAFSA will iterate L times to estimate parameters for all paths, the mainly difference of computation lies in the process of one iteration. So we will focus on the computation of one iteration.

For OMP algorithm, let K_L be the length of the preamble, $N = N\tau\ Na$ be the total number of delay-scaled versions of preamble, that is, the column dimensions of the dictionary. Thus, the inner products of the received signal and columns in the dictionary requires $\rho = NK_L$ complex multiplications. For channel 1, $N\tau = 250$, $Na = 200$, thus $N = 5 \times 10^4$, while for channel 2, $Na = 100$, and $N = 2.5 \times 10^4$.

For IAFSA, each iteration includes $k$max sub-iterations, and during each sub-iteration, P fish will be involved and each fish will do swarming and following. For the worst case, that is, both swarming and following fail to find a better position, fish will turn to preying, and this requires to calculate inner products of the received signal and the delay-scaled version $2I$ times. Thus, the whole computation is $\rho = K_L P k_{\max} 2I$. For both channel 1 and 2, $P = 50$, $k$max $= 10$ and $I = 10$. So, $\rho = 1 \times 10^4$.

From the above analysis, the computational complexity of IAFSA is much lower than OMP algorithm, especially when the delay spread and Doppler spread are large, which is the case of UWA channel.

5 Conclusion

We have invested the problem of Doppler-distorted UWA channels estimation in this paper and propose the IAFSA method. In particular, during each iteration, a sub-iteration is included and we propose to adjust the step and fish's positions during the sub-iteration to search more carefully around the optimal solution. And the estimated signal component will be eliminated from the received signal for next iteration. The new method has the advantages of faster convergence and finer resolution compared with OMP algorithm. The simulation results show that IAFSA outperforms OMP in estimation accuracy as well as has a lower computational complexity.

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