IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 7, 2017, accepted 28, 2017, date of publication March 10, 2017, date of current version April 24, 2017.

*Digital Object Identifier 10.1109/ACCESS.2017.2681101*

# Parameter Estimation for Multi-Scale Multi-Lag Underwater Acoustic Channels Based on Modified Particle Swarm Optimization Algorithm

**XING ZHANG[1], KANG SONG[2,1], (Member, IEEE), CHUNGUO LI[1], (Senior Member, IEEE), AND LUXI YANG[1], (Member, IEEE)**

[1]Key Laboratory of Underwater Acoustic Signal Processing of Ministry of Education, Southeast University, Nanjing 210096, China
[2]School of Electronic and Information Engineering, Qingdao University, Qingdao 266071, China

Corresponding authors: C. Li (chunguoli@seu.edu.cn) and X. Zhang (220150713@seu.edu.cn).

This work was supported in part by the National Basic Research Program of China (973) under Grant 2013CB336600, in part by the National Natural Science Foundation of China under Grant 61671144, Grant 61372101, and Grant 61521061, in part by the National High Technology Research and Development Program of China (863) under Grant 2014AA01A704, in part by the Fundamental Research Funds for the Central Universities and the Open Research Fund of Key Lab of Broadband Wireless Communications and Sensor Network Technologies, Ministry of Education under Grant NYKL201502, and in part by the Funding of Supporting Excellent Young Professors for Teaching and Research in Southeast University.

**ABSTRACT** The wideband underwater acoustic multipath channel can be modeled as a multi-scale multi-lag (MSML) channel because signals from different paths might experience different Doppler scales. This brings great challenge to channel parameter estimation. In this paper, we propose a novel algorithm for parameter estimation of MSML channels. This new algorithm is a modified particle swarm optimization (MPSO) algorithm, which can estimate the parameters of the Doppler scale, the time delay, and the amplitude simultaneously for each individual path. Comparing to PSO algorithm, MPSO algorithm uses a multipath list to record positions and fitness values of particles whose fitness values are selected as *lbest*s, and uses these *lbest*s to update particles' velocities at each iteration. As for training sequence, we employ the zero correlation zone sequence which has excellent correlation properties. Computer simulation is used to evaluate the proposed algorithm in comparison with the matching pursuit (MP)-based method and the fractional Fourier transform (FrFT)-based method. Simulation results confirm that the proposed MPSO algorithm outperforms both MP-based method and FrFT-based method in estimation accuracy as well as computation complexity.

**INDEX TERMS** Multi-scale multi-lag (MSML) channel, parameter estimation, modified particle swarm optimization (MPSO) algorithm, zero correlation zone (ZCZ) sequence.

## I. INTRODUCTION

Underwater acoustic (UWA) communication has attracted considerable attention and investigation recently [1]–[4]. The demand for high-quality UWA communications arises in many military, scientific and civilian applications [5], [6]. However, at the physical layer, effective communications for UWA channels is quite challenging for large multipath spread and significant Doppler effects, which are caused by the motion of platform and sea-surface [7]. Specifically, on the one hand, due to the low propagation speed at 1500m/s of acoustic waves, multipath spread leads to long time delay characteristic of the UWA channels and severe inter-symbol interference (ISI) when received signals from different paths collapse into each other [8], [9]. On the other hand, low propagation speed of acoustic waves also results in more significant Doppler effects in UWA communication than in terrestrial wireless systems whose carrier propagates at $3 \times 10^8$m/s. Doppler effects can be treated as Doppler shift in terrestrial wireless system which is narrowband, i.e., the signal bandwidth is far less than the carrier frequency [10]. However, for UWA systems, the ratio between bandwidth against carrier frequency is usually 1000 times greater than that of terrestrial wireless systems. Thus, the UWA channel is wideband in nature and Doppler effects could have different values for different frequencies throughout the bandwidth. Due to its nature, Doppler effects should be treated as Doppler scale [2], [11], which cause signal compressing or dilating in time domain. Furthermore, the Doppler scale of each path might be different owing to distinct angles of arrival in the UWA environment as observed in experiments [12]–[14]. So we adopt the multi-scale multi-lag (MSML) channel model denoted in [15] in this paper.

The MSML channel model arose in the last few years of the 2000s and has the optimal performance in dynamic water circumstances with multipath. One possible approach to achieving the MSML channel model is to parameterize the amplitude, the time delay and the scale factor in a path-wise manner [5]. However, using the path-based model, with the increase of path number, problems arise such as computational complexity. A remedy to these problems is to exploit the sparse structure of the UWA channels, which means that only a few paths are dominant in energy while others could be neglected [16], [17]. So only the dominant paths' parameters need to be concerned while the rest could be neglected for UWA channel estimation.

The parameters for UWA channel estimation include the scale factor, the time delay and the amplitude. Among these three parameters, the scale factor is widely considered to be the most difficult to accommodate for the wideband nature of UWA channel, where estimation methods for terrestrial wireless system can not be applied. Therefore, it attracts many researchers and different Doppler estimation methods have been proposed for UWA communication. [18] proposes the block Doppler estimation method, which can be realized by measuring the duration change of a known signal, usually the linear frequency modulation (LFM) signal. The estimation accuracy relies on the length of the LFM signal. The longer the preamble is, the more accurate scale estimation we can get. However, the length increase of the preamble will reduce the communication efficiency. [10] puts forward an improved method by using block Doppler estimation as the coarse estimation, and by minimizing the energy of null subcarriers to estimate residual Doppler effects. Furthermore, [19] adopts hyperbolic frequency modulation (HFM) signal as preamble instead of LFM signal in [18], because HFM signal has better Doppler-invariant property. In [20], ambiguity function method is proposed, which employs a bank of correlators at the receiver to get the ambiguity function of the received pseudo-random noise (PN) sequence.The range and resolution of the Doppler estimate depend on the number of correlators used. More correlators need additional hardware overhead. Based on [20], [2] proposes the use of multicarrier waveforms as the preamble which includes two identical orthogonal frequency division multiplexing (OFDM) symbols. A joint synchronization and Doppler scale estimation method with dual PN padding time domain synchronous orthogonal frequency division multiplexing (TDS-OFDM) is given in [11], which involves a two-dimensional searching that can estimate the time delay and Doppler scale simultaneously at the expense of high computation complexity.

However, all of the aforementioned methods only consider one dominant scale factor. In MSML channel model, such scale estimation and compensation mechanism will leave residual sampling errors to other scaled components. Therefore, the challenge of MSML channel estimation is to identify the parameters for each individual path. At present, the estimation methods for MSML cases can be divided into two groups. One is the compressed-sensing (CS) based sparse channel estimation and the other is fractional Fourier transform (FrFT) based channel estimation.

Based on CS, [12], [16], [21]–[24] search for those optimal parameters within a predefined dictionary with the assistance of those greedy algorithms. The intension of those greedy algorithms is to iteratively search for the optimal estimation, while basis pursuit (BP) and orthogonal matching pursuit (OMP) are two applications. Specifically, in [21] and [22], MP algorithm is used to distinguish paths featuring different Doppler scale factors. The parameters of each path are estimated by finding the columns of the dictionary which are most relevant with the received signal. Then the received signal updates itself by eliminating the estimated path components. Based on MP, the order-recursive least squares MP (LS-MP) algorithm developed in [16] selects the column according to the LS error at each iteration, instead of picking the most relevant column as the MP algorithm does. [12] introduces both MP and its orthogonal version, the OMP algorithm, and makes comparison with traditional subspace methods. Both MP and OMP algorithms perform better than subspace methods. To reduce the computational complexity, [23] proposes to use fast block-Fourier transform in OMP algorithm, and a two-stage OMP algorithm is developed in [24], which sequentially estimates the delay and Doppler scale factor. However, all the CS-based methods have a common deficiency: using a fixed dictionary to approximate the target signal. Thus, a fine resolution will be at the expense of large dictionary and extensive calculation.

LFM signals are chosen as preamble for FrFT methods because the LFM signal will become an impulse signal in the FrFT domain with an appropriate rotation. A method proposed in [25] can estimate the delay and scale factor according to the locations and widths of the peaks of the received LFM signal in the FrFT domain. [26] develops a coarse-to-fine method to search for the optimal fractional order of LFM signal's FrFT and the scale can be calculated according to the optimal fractional order change of the transmitted and the received LFM signals. Based on [26], [27] proposes an iterative algorithm to estimate parameters of each path and then separate it from the received signal. A sub-iteration is used to adjust the optimal fractional order at each iteration, which is found by the method in [26]. The biggest drawback of the FrFT based method is the poor time resolution of the LFM signal [2], which will lead to inaccurate time delay estimate and influence the estimate accuracy of the scale.

According to the above analyses, a novel parameters estimation scheme is proposed in this paper, and we call it modified particle swarm optimization (MPSO) algorithm. The PSO algorithm is one of the intelligent algorithms which has many advantages, such as high efficiency, fast search speed and simple algorithm [28]. In PSO, each individual is called a particle and represents a potential optimal solution in the optimization problems. At each iteration, particles move in the solution space to search for better fitness values and update their positions and velocities according to their own best values achieved so far, called *pbest*s, and the whole swarm best value, called *gbest*. Directly applying PSO algorithm can only find out the parameters of the strongest path. So we propose the MPSO algorithm for MSML channel estimation. In comparison with PSO, MPSO algorithm has the following distinctions:

1) Each particle's position represents a possible pair of scale factor and time delay. At the initialization period, a multipath list is formed by selecting particles whose fitness values are greater than a threshold. These fitness values in the multipath list are called *lbest*s.
2) At each iteration, each particle updates its position and velocity according to its *pbest* and the *lbest* in the multipath list whose time delay is nearest to the particle's.
3) At each iteration, the multipath list will also be updated after recalculating the fitness value of each updated particle.

The contributions of this paper are the following:

1) We propose a novel algorithm which is called MPSO algorithm for the parameter estimation of MSML channel.
2) We propose to use zero correlation zone (ZCZ) sequence [29] as the training sequence and analyze its correlation properties. The excellent properties of the ZCZ sequence can benefit the performance of MPSO algorithm.
3) We use extensive numerical simulations to investigate the performance of the proposed algorithm, and make comparisons with MP-based and FrFT-based methods.
4) We present the performance analysis and complexity analysis of the proposed algorithm as well as MP-based and FrFT-based algorithms in detail.

The rest of this paper is organized as follows. Section II gives the system model and a introduction of the ZCZ sequence. In Section III we present the PSO and the proposed MPSO algorithms, respectively. In Section IV we analyze MPSO-based MSML channel parameters estimation method. And computer simulation is given in Section V. Finally, we conclude in Section VI.

*Notation*: we will use the following notations in this paper: Upper (lower) bold-face letters stand for matrices (vectors); Superscript $*$ denotes conjugate. We use $\mathrm{Re}\{\cdot\}$ for the real part, $[\mathbf{A}]_{k,m}$ for the $(k,m)$th entry of matrix $\mathbf{A}$, and $\delta(t)$ for a delta function which is equal to one only if $t = 0$ and zero otherwise.

## II. SYSTEM MODEL

OFDM is widely used in UWA communication whose available bandwidth is limited. Further, to reduce power consumption of the guard interval between OFDM symbols, we consider zero-padded (ZP) OFDM as the basic signalling format as in [2], [12], and [23]. Specifically, let $T$ denote the duration of an OFDM symbol and $T_g$ denote the guard interval. Then $T' = T + T_g$ is the duration of the whole OFDM block and $1/T$ is the subcarrier spacing. The $k$th subcarrier is at frequency

$$f_k = f_c + k/T, \quad k = -K/2, \ldots, K/2-1 \tag{1}$$

where $f_c$ is the carrier frequency and $K$ is the number of subcarriers, so the bandwidth is $B = K/T$. Data streams are encoded with a nonbinary low-density parity-check (LDPC) code. And after quadratic phase-shift-keying (QPSK) or quadratic amplitude modulation (QAM), the information symbol transmitted on the $k$th subcarrier is $s[k]$. The signal in baseband can be written as

$$x(t) = \sum_{k=0}^{K-1} s[k] e^{j2\pi \frac{k}{T} t} q(t), \quad t \in [-T_g, T] \tag{2}$$

where $q(t)$ is the pulse shaping filter and we use the rectangular pulse shaper in this paper, that is

$$q(t) = \begin{cases} 1 & t \in [0, T] \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

and the corresponding passband signal is

$$\tilde{x}(t) = \mathrm{Re}\left\{ e^{j2\pi f_c t} \sum_{k=0}^{K-1} s[k] e^{j2\pi \frac{k}{T} t} q(t) \right\}, \quad t \in [-T_g, T] \tag{4}$$

### A. CHANNEL MODEL

The channel impulse response for a time-varying multipath underwater acoustic channel can be modeled as a MSML channel, that is

$$h(\tau, t) = \sum_{l=1}^{L} A_l(t) \delta(\tau - \tau_l(t)) \tag{5}$$

where $L$ is the number of channel taps. $A_l(t)$ and $\tau_l(t)$ are the time-varying path amplitude and time delay of the $l$th path. $\tau_l(t)$ is caused by platform motion and scattering off of the moving sea surface. $A_l(t)$ change with $\tau_l(t)$ because the path attenuation is related to travel distance and the physics of the scattering and propagation processes [12].

For the duration of one OFDM symbol, $\tau_l(t)$ can be represented by a Doppler scale factor $a_l$ as

$$\tau_l(t) = \tau_l - (a_l - 1)t \tag{6}$$

and $A_l(t)$ is assumed to be constant: $A_l(t) \approx A_l$. With this, we simplify the channel model as

$$h(\tau, t) = \sum_{l=1}^{L} A_l \delta(\tau - (\tau_l - (a_l - 1)t)) \tag{7}$$

and the passband signal at the receiver is

$$\tilde{y}(t) = \sum_{l=1}^{L} A_l \tilde{x}(a_l t - \tau_l) + \tilde{n}(t), t \in [-T_g, \frac{T}{a_l}] \tag{8}$$

where $\tilde{n}(t)$ is the additive noise.

### B. RECEIVER PROCESSING

Performing down conversion and ZP-OFDM demodulation, the output $y_m$ is

$$y_m = \frac{1}{T}\int_0^{T/a_l} \tilde{y}(t)e^{-j2\pi f_c t}e^{-j2\pi \frac{m}{T}t}dt \tag{9}$$

Plugging in $\tilde{y}(t)$, we simplify $y_m$ to

$$y_m = \sum_{l=1}^{L}\frac{A_l}{a_l}e^{-j2\pi f_c\tau_l}\sum_{k=1}^{K-1}s[k]e^{-j2\pi\frac{k}{T}\tau_l} \times \text{sinc}(\beta_{k,m}^l T)e^{j\pi\beta_{k,m}^l T} + n_m \tag{10}$$

where $n_m$ is the additive noise and

$$\beta_{k,m}^l = (k-m)\frac{1}{T} + \frac{(a_l-1)f_m}{a_l} \tag{11}$$

The formula deduction can be seen in Appendix A.

Defining $\mathbf{y}$ as the received vector , $\mathbf{s}$ as the data vector and $\mathbf{n}$ as the noise vector across all subcarriers, the input-output relationship can be written as following:

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{n} \tag{12}$$

where $\mathbf{H}$ is the channel mixing-matrix and can be expressed as

$$\mathbf{H} = \sum_{l=1}^{L}\xi_l\Lambda_l\Gamma_l \tag{13}$$

where $\xi_l$ is the complex path gain for the $l$th path and is expressed as

$$\xi_l = \frac{A_l}{a_l}e^{-j2\pi f_c\tau_l} \tag{14}$$

$\Lambda_l$ is a $K \times K$ diagonal matrix whose $(k, k)$th entry is

$$[\Lambda_l]_{k,k} = e^{-j2\pi\frac{k}{T}\tau_l} \tag{15}$$

And $\Gamma_l$ is a $K \times K$ non-diagonal matrix, and its non-zero off-diagonal elements represent the inter-carrier interference (ICI). The $(k, m)$th element is

$$[\Gamma_l]_{k,m} = \text{sinc}(\beta_{k,m}^l T)e^{j\pi\beta_{k,m}^l T} \tag{16}$$

The formulation in (13) clearly specifies the contribution from each discrete path with delay $\tau_l$ and Doppler scale $a_l$ towards the channel mixing matrix that defines the ICI pattern [12]. So estimating channel parameters accurately has important implications for the coherent OFDM performance.

### C. TRAINING SEQUENCE

We consider to apply ZCZ sequence as the training sequence. ZCZ sequence set is first introduced in code division multiple access (CDMA) system to enhance timing synchronization robustness [30], [31]. It has shown that ZCZ sequence is the optimal channel estimation training sequence [32]–[34].

Let $S$ be a sequence set with $M$ sequence of period $P$ and be expressed as

$$S = \{S_0, S_1, S_2, \ldots, S_u, \ldots, S_{M-1}\} \tag{17}$$
$$S_u = \{s_0^u, s_1^u, s_2^u, \ldots, s_v^u, \ldots, s_{P-1}^u\} \tag{18}$$

where $0 \le u \le M-1, 0 \le v \le P-1$, $S_u$ and $s_v^u$ denote a sequence and a sequence element respectively.

If all of the sequences in the set $S$ satisfy the auto-correlation and cross-correlation properties in the following, then $S$ can be called as a set of ZCZ sequences or a ZCZ sequence set [35]:

$$R_{S_{u0}}(\tau) = \sum_{v=0}^{P-1}s_v^{u0}(s_{(v+\tau)\bmod P}^{u0})^* = \begin{cases}E_{u0} & (\tau=0)\\ 0 & (-T_0 \le \tau \le -1, 1 \le \tau \le T_0)\end{cases} \tag{19}$$

$$R_{S_{u0},S_{u1}}(\tau) = \sum_{v=0}^{P-1}s_v^{u0}(s_{(v+\tau)\bmod P}^{u1})^* = 0 \quad (-T_0 \le \tau \le T_0) \tag{20}$$

where $R_{S_{u0}}(\tau)$ is the periodic auto-correlation function of the sequence $S_{u0}$, and $R_{S_{u0},S_{u1}}(\tau)$ $(u0 \neq u1)$ is the periodic cross-correlation function between the sequences $S_{u0}$ and $S_{u1}$. $E_{u0}$ is the energy of the sequence $S_{u0}$ [35] and is defined as following:

$$E_{u0} = \sum_{v=0}^{P-1}s_v^{u0}(s_v^{u0})^* = \sum_{v=0}^{P-1}|s_v^{u0}|^2 \tag{21}$$

Here, $M, P$ and $T_0$ represent the family size of the ZCZ sequence set, the period of the sequences, and the length of the ZCZ, respectively [35].

## III. MODIFIED PARTICLE SWARM OPTIMIZATION (MPSO) ALGORITHM

UWA multipath channels are sparse both in time domain and frequency domain [12], [16], [27], which means that only some taps are nonzero in the channel model and we can set $L$ as a small positive integer in (7). Therefore, only $L$ sets of parameters need to be estimated and the calculation complexity is significantly reduced. Furthermore, it is possible that those $L$ paths can be identified by a modified PSO algorithm.

### A. PSO ALGORITHM

PSO was introduced in 1995 by Kennedy and Eberhart [36]. The original intent was to graphically simulate the graceful but unpredictable choreography of a bird flock. The system of PSO is initialized with a population of random solutions and each potential solution is assigned a randomized velocity, and the potential solutions, called particles, are then "flown" through the problem space.

In the problem space, each particle updates its position according to two "best" values. One is the best solution itself has achieved so far, called *pbest*; and the other is the best solution tracked by all particles in the swarm, called *gbest*.

A brief introduction to the operation of the PSO algorithm is as follows. Let $p$ denote the number of particles in the swarm and each particle's position represents a potential solution of the problem space $D$. At the $(k+1)$th iteration, for particle $i$, its position $x_{k+1}^i$ can be calculated as follows:

$$x_{k+1}^i = x_k^i + v_{k+1}^i \tag{22}$$

with a pseudo-velocity $v_{k+1}^i$ calculated in the following manner:

$$v_{k+1}^i = \omega_k v_k^i + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (p_k^g - x_k^i) \tag{23}$$

Where $\omega_k$ is an inertia weight which was developed to better control exploration and exploitation. Suitable selection of $\omega_k$ provides a balance between global and local exploration and exploitation, thus accelerates the algorithm convergence speed. $p_k^i$ is the position corresponding to *pbest* of particle $i$ at the $k$th iteration, and $p_k^g$ represents the position of *gbest* at the $k$th iteration. $r_1$, $r_2$ are random numbers between 0 and 1. $c_1$ and $c_2$ are the acceleration constants that pull each particle toward *pbest* and *gbest* positions and can be set as $c_1 = c_2 = 2$. The purpose of calculating $v_{k+1}^i$ as in (23) is to maintain separation of particles in the group and to search a greater space.

The following is the process for implementing the PSO algorithm in detail, the iteration will stop when a criterion is met, usually a maximum number of iterations or a sufficiently good fitness. Here, we use a fixed number of swarm iterations as the stopping criteria.

1. Initialize
 (a) Set constants $c_1, c_2, \omega_k$, the maximum velocity $v_{\max}$ and maximum iterations $k_{\max}$, set counters $k = 0$.
 (b) Initialize a population of particles with random positions $x_0^i \in D$ for $i = 1, \cdots, p$ and velocities $0 \le v_0^i \le v_{\max}$ for $i = 1, \cdots, p$.
 (c) Evaluate fitness values $f_0^i$ using initialized positions $x_0^i$ for $i = 1, \cdots, p$.
 (d) Set $f_{best}^i = f_0^i, p_0^i = x_0^i$ for $i = 1, \cdots, p$.
 (e) Set $f_{best}^g$ to best $f_{best}^i$ and $p_0^g$ to corresponding $x_0^i$.
2. Optimize
 (a) Update particle velocity vector $v_{k+1}^i$ using Equation (23) and if $v_{k+1}^i > v_{\max}$ then set $v_{k+1}^i = v_{\max}$, for $i = 1, \cdots, p$.
 (b) Update particle position $x_{k+1}^i$ according to Equation (22) for $i = 1, \cdots, p$.
 (c) Evaluate fitness value $f_{k+1}^i$ using $x_{k+1}^i$, for $i = 1, \cdots, p$.
 (d) If $f_{k+1}^i$ is better than $f_{best}^i$ then $f_{best}^i = f_{k+1}^i, p_{k+1}^i = x_{k+1}^i$ else $p_{k+1}^i = p_k^i$, for $i = 1, \cdots, p$.
 (e) If $f_{k+1}^i$ is better than $f_{best}^g$ then $f_{best}^g = f_{k+1}^i, p_{k+1}^g = x_{k+1}^i$ else $p_{k+1}^g = p_k^g$, for $i = 1, \cdots, p$.
 (f) Set $k = k + 1$ and loop to step 2(a) until $k > k_{\max}$.

Particle's velocity on each dimension are clamped to a maximum velocity $v_{\max}$ which is a parameter specified by the user. If the velocity on one dimension would exceed $v_{\max}$, then it will be limited to $v_{\max}$.

### B. MPSO ALGORITHM

Let each particle's position represent a possible pair of $\{a_l, \tau_l\}$. The optimal Doppler scale factor and time delay can be found out by PSO algorithm. So PSO algorithm can be applied in signal detection and channel parameters estimation. However, PSO algorithm can only find out the parameters of the strongest path as all particles are searching for *gbest*. For MSML channel, parameters of each individual path need to be identified, thus some modifications are necessary. This paper proposes a modified PSO (MPSO) algorithm. In MPSO, we distinguish two paths by the difference value of time delay, i.e., the difference value of time delay of two paths should satisfy the following formula:

$$|\tau_i - \tau_j| > \Delta_{peak}, i \ne j \tag{24}$$

where $\Delta_{peak}$ is the set threshold. For each path, its fitness value will be the maximum fitness value of particles which are divided into the same path. And we use *lbest* to update particle's velocity instead of *gbest*. The process for implementing the MPSO algorithm is as follows:

1. Initialize
 (a) Set constants $c_1, c_2, \omega_k$, the maximum velocity $v_{\max}$ and maximum iterations $k_{\max}$, set counters $k = 0$.
 (b) Initialize a population of particles with random two-dimensional positions $x_0^i \in D$ for $i = 1, \cdots, p$ and two-dimensional velocities $0 \le v_0^i \le v_{\max}$ for $i = 1, \cdots, p$.
 (c) Evaluate fitness values $f_0^i$ using $x_0^i$ for $i = 1, \cdots, p$. And if $f_0^i > thr1$, $x_0^i$ and corresponding $f_0^i$ will be added to a multipath list and be written as $p_{lbest}^i$ and *lbest(i)* respectively.
 (d) Set $f_{best}^i = f_0^i, p_0^i = x_0^i$ for $i = 1, \cdots, p$.
2. Optimize
 (a) For each particle $i$, find out the nearest $\tau_l$ from the multipath list. If $f_k^i < lbest(l)$ then skip to step 2(b) else skip to step 2(c).
 (b) Update particle velocity using the following equation:

$$v_{k+1}^i = \omega_k v_k^i + c_1 r_1 (p_k^i - x_k^i) + c_2 r_2 (p_{lbest}^l - x_k^i)$$

 where $p_{lbest}^l$ is the position of the *lbest(l)*, and update particle position using Equation (22).
 (c) Update particle velocity using the following equation:

$$v_{k+1}^i = \omega_k v_k^i + c_1 r_1 (p_k^i - x_k^i)$$

 and update particle position using Equation (22).
 (d) Set $i = 0$.
 (e) Evaluate fitness value $f_{k+1}^i$ using $x_{k+1}^i$.
 (f) If $f_{k+1}^i > \min(lbest)$ then skip to step 2(g), else set $i = i + 1$ and skip to step 2(e).
 (g) Find out the nearest $\tau_l$ from the multipath list and calculate the difference value of time delay: $\Delta_\tau = |\tau_i - \tau_l|$.
 (h) If $\Delta_\tau > \Delta_{peak}$ then add $x_{k+1}^i$ and corresponding $f_{k+1}^i$ to the multipath list to represent another possible path. And update particle best value $f_{best}^i$ and position $p_{k+1}^i$, skip to

step 2(j), else update particle best value $f^i_{best}$ and position $p^i_{k+1}$, skip to step 2(i).

(i) If $lbest(l) < f^i_{k+1}$, then update *lbest*.

(j) If $i > p$, then set $k = k + 1$ and skip to step 2(k), else set $i = i + 1$ and skip to step 2(g).

(k) Loop to step 2(a) until $k > k_{\max}$.

(l) Select $\{a_l, \tau_l\}$ from the multipath list whose $lbest(l) > thr2$, consequently, $\{a_l, \tau_l\}$ are the Doppler scale factor and the time delay of path $l$ respectively.

Note: $\Delta_{peak}$, $thr1$ and $thr2$ are three thresholds we need to set for this algorithm. $\Delta_{peak}$ is set as the minimum difference of time delay that can distinguish two paths. $thr1$ is the normalized threshold for the initializing of the multipath list and its value can be a small positive number, usually 0.1 or 0.2. $thr2$ is the normalized energy threshold used to select parameters from the multipath list. It is set according to the desired signal to noise ratio (SNR).

## IV. MPSO-BASED MSML CHANNEL PARAMETERS ESTIMATION

Consider a MSML channel model, the discrete-time signal at the receiver is expressed as

$$\mathbf{r} = \sum_{l=0}^{L-1} \mathbf{s}_l h_l + \mathbf{n} \tag{25}$$

where $\mathbf{s}_l = [s_0, s_1, \cdots, s_{P-1}]^T$ is the training sequence on the $l$th path and $P$ denotes the period of the sequence. $h_l$ denotes the $l$th discrete-time channel impulse response (CIR). $\mathbf{n}$ denotes a noise vector with mean zero and variance $\sigma^2$. For ease of deduction, the form of (25) can be rewritten as

$$\mathbf{r} = \mathbf{Sh} + \mathbf{n} \tag{26}$$

where $\mathbf{S} = [\mathbf{s}_0, \mathbf{s}_1, \cdots, \mathbf{s}_l, \cdots, \mathbf{s}_{L-1}]$ and $\mathbf{h} = [h_0, h_1, \cdots, h_l, \cdots, h_{L-1}]^T$. The least square (LS) estimator of $\mathbf{h}$ is given by

$$\hat{\mathbf{h}} = (\mathbf{S}^H\mathbf{S})^{-1}\mathbf{S}^H\mathbf{r} \tag{27}$$

Note that $\mathbf{h} = (\mathbf{S}^H\mathbf{S})^{-1}\mathbf{S}^H(\mathbf{r} - \mathbf{n})$, then the mean square error (MSE) of $\mathbf{h}$ can be expressed as

$$\begin{aligned} MSE &= \frac{1}{L} tr\{E\{(\hat{\mathbf{h}} - \mathbf{h})(\hat{\mathbf{h}} - \mathbf{h})^H\}\} \\ &= \frac{\sigma^2}{L} tr\{(\mathbf{S}^H\mathbf{S})^{-1}\} \end{aligned} \tag{28}$$

To minimize the MSE, that is, to reach classical Cramer-Rao lower bound (CRLB), $\mathbf{S}^H\mathbf{S}$ should satisfy the following formula:

$$\mathbf{S}_i^H\mathbf{S}_j = \begin{cases} E_{\mathbf{s}_i,\mathbf{s}_j}\mathbf{I}_L, & i = j \\ \mathbf{0}_L, & i \neq j \end{cases} \tag{29}$$

where $E_{\mathbf{s}_i,\mathbf{s}_j} = \mathbf{s}_i^H\mathbf{s}_j$, $\mathbf{I}_L$ is a $L \times L$ unit matrix and $\mathbf{0}_L$ is a $L \times L$ zero matrix. The sequence set satisfying (29) is called an optimal training sequence set [29].

Formula (29) can also be rewritten as

$$\begin{aligned} R_{\mathbf{s}_i,\mathbf{s}_j}(\tau) &= \sum_{n=0}^{P-1} s_i^n (s_j^{(n+\tau) \bmod P})^* \\ &= \begin{cases} E_{\mathbf{s}_i,\mathbf{s}_j} & (\tau = 0, i = j) \\ 0 & (0 < |\tau| \leq T_L, i = j) \\ 0 & (0 < |\tau| \leq T_L, i \neq j) \end{cases} \end{aligned} \tag{30}$$

where $T_L$ is the maximum time delay of all paths. Then it is clear that ZCZ sequence meets (30) based on the definition in part II.C. So it means that ZCZ sequence can serve as the optimal training sequence and can be in favor of MPSO algorithm for channel estimation.

### A. ESTIMATION OF THE SCALE FACTOR AND THE TIME DELAY

Denoting $r(t)$ as the received training sequence and $s_{Local}(t)$ as the local ZCZ sequence, and denoting $s_{Local}^{(a_i,\tau_i)}(t) = s_{Local}(a_i t - \tau_i)$ as the resampled-delay version of $s_{Local}(t)$ with $a_i$ as the resampling factor and $\tau_i$ as the time delay, the cross-correlation value of $r(t)$ and $s_{Local}^{(a_i,\tau_i)}(t)$ is given by

$$\begin{aligned} < r, s_{Local}^{(a_i,\tau_i)} > &= A_i \int_{-\infty}^{+\infty} s_i(t) s_{Local}(a_i t - \tau_i) dt \\ &\quad + \sum_{l=1, l\neq i}^{L} A_l \int_{-\infty}^{+\infty} s_l(t) s_{Local}(a_i t - \tau_i) dt \\ &\quad + \int_{-\infty}^{+\infty} n(t) s_{Local}(a_i t - \tau_i) dt \end{aligned} \tag{31}$$

According to the auto-correlation and cross-correlation properties of ZCZ sequence, we can know that if the parameters $\{a_i, \tau_i\}$ are available, the first term of the right-hand side of (31) is approximately equal to $E_{\mathbf{s}_i,\mathbf{s}_i}$, the peak value of path $i$, and the second term approaches to zero. So we can distinguish different paths and deal with signals from MSML channel.

(31) can be solved by brute force approach, that is, trying all possible combinations of $\{a_i, \tau_i\}$ and the best solution will be the one with the maximum cross-correlation value. But this needs high computation cost, and the accuracy is limited by the step size, in the exhaustive search it may jump over the peak if the step is not appropriate.

In MPSO, each particle's position represents a possible pair of $\{a_i, \tau_i\}$ and parameters of Doppler scale and time delay can be get simultaneously once a particle reaches the *lbest*. We can get all paths parameters from the multipath list at the end of iterations. Comparing with the brute force approach, on the one hand, each particle can update its position and velocity according to the nearest *lbest*, thus this algorithm features high speed of convergence. On the other hand, MPSO can search more precisely around the peak for the velocity will be dynamically adjusted in each iteration. Furthermore, MPSO is shown to be robust as it introduces random factors.

### B. ESTIMATION OF THE AMPLITUDE

From (31) we can know that the cross-correlation function of ZCZ sequence can reach a sharp peak if $s_{Local}(a_i t - \tau_i)$ matches the received signal $s_i(t)$ well. Therefore, once the scale factor and time delay are estimated using MPSO algorithm, then the amplitude $A_i$ can be estimated through calculating the cross-correlation between $s_{Local}^{(a_i \tau_i)}(t)$ and $r(t)$, i.e.

$$\hat{A}_i = \frac{\int_{-\infty}^{+\infty} r(t) s_{Local}^{(a_i,\tau_i)}(t)dt}{\int_{-\infty}^{+\infty} ||s_{Local}^{(a_i,\tau_i)}(t)||^2 dt} \tag{32}$$

In fact, it is exactly the fitness value of the corresponding $\{a_i, \tau_i\}$ in the multipath list. So the triplet of $\{a_i, \tau_i, A_i\}$ can be get simultaneously from the multipath list.

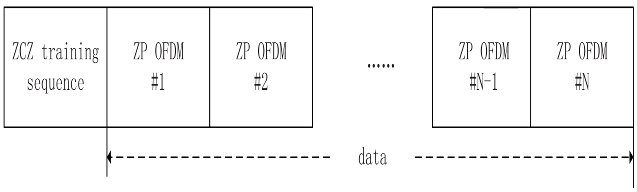



**FIGURE 1.** The structure of the data packet.

## V. SIMULATION RESULTS

In this section, we use computer simulation to evaluate the proposed MPSO algorithm. Firstly, we will give a brief introduction about the ZCZ sequence and simulation parameters adopted in this paper. Secondly, we evaluate and analyse the performance of the MPSO algorithm with different evaluation criteria. And comparisons with other estimation methods will also be included. Finally, we will give out the complexity analysis of MPSO algorithm as well as make comparisons with other estimation methods.

### A. SIMULATION SETUP

The length of the ZCZ sequence we adopt in the simulation is 512. The data packet structure used and the property of ZCZ sequence are demonstrated in Fig.1 and Fig.2 respectively.

From Fig.2 in the next page, we can see that ZCZ sequence has very good correlation properties, i.e., it reaches a sharp peak if the local sequence matches the receive signal well and nearly zero for other cases.

We will use the path-based model to emulate the real MSML underwater acoustic channel which is sparse in nature.

$$h(\tau, t) = \sum_{l=1}^{L} A_l \delta(a_l t - \tau_l) \tag{33}$$

And we will use similar assumptions as the ones in references [15]–[17], [21]–[24]. For the sparsity of UWA channel, only a few of quantized channel parameters need to be considered and estimated, which is supported by many underwater communication experiment data as presented in [2], [10], [12], and [13].

1) Set path number $L = 8$, and the amplitudes of these paths are uniformly distributed.
2) The scale factors $a_l (l = 1, 2, \cdots L)$ are uniformly distributed within $a_l \in [1, a_{\max}]$, with an accuracy to three decimal places. Here, we set $a_{\max} = 1.02$ which corresponds to a relative velocity about 30 knots and is relatively high for underwater movement [27].
3) The delays follow uniformly distribution and all the paths arrive at the receiver within one signal duration $T$ [27].

Although the values of $A_l, a_l, \tau_l$ are assumed to stay constant during sone signal duration $T$, they result in a wideband channel which varies with time.

The ZP-OFDM specifications are summarized in Table 1.

**TABLE 1.** Parameters of ZP-OFDM in numerical simulation.

| Parameter | value |
|---|---|
| carrier frequency ($f_c$) | 13kHz |
| bandwidth ($B$) | 9.77kHz |
| no.subcarriers ($K$) | 1024 |
| symbol duration ($T$) | 104.86ms |
| subcarrier spacing ($\Delta f$) | 9.54Hz |
| guard interval ($T_g$) | 24.6ms |

The data rate, $R$, also depends on the modulation scheme and the number of OFDM symbols, $N$, transmitted in each packet. We adopted 10 symbols in each packet and use a rate 1/2 nonbinary LDPC code to encode data. Using a 16-QAM modulation, the spectral efficiency $\lambda$ and the data rate $R$ can be calculated by

$$\lambda = \frac{T}{T+T_g} \cdot \frac{N \times 1024}{N \times 1024 + 512} \cdot \frac{1}{2} \cdot \log_2 16 = 1.5\text{bits/s/Hz} \tag{34}$$

$$R = \lambda B = 14.7\text{kb/s} \tag{35}$$

At the receiver, in MPSO algorithm, each particle's position, $\{a_i, \tau_i\}$, can be used to modulate the local ZCZ sequence and get a scale-delay version, $s_{\alpha_i}$, to match the receive ZCZ sequence, $r$. At the optimizing step, we will select particles according to their fitness values:

$$M = |C|^2 / E^2 \tag{36}$$

where

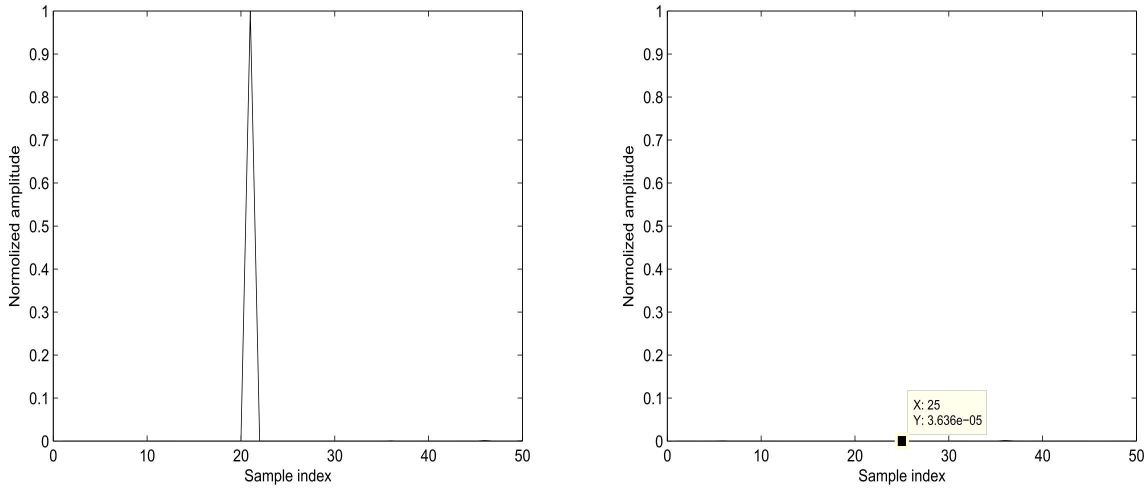
$$C = \sum_{k=0}^{K_z - 1} r(\tau_i + k) \cdot {s_{\alpha_i}}^*(k) \tag{37}$$

$$E = \sum_{k=0}^{K_z - 1} s_{a_i}(k) \cdot {s_{a_i}}^*(k) \tag{38}$$

where $K_z$ is the length of $s_{\alpha_i}$. And parameters adopted in MPSO are listed in table 2.

### B. PERFORMANCE OF CHANNEL PARAMETER ESTIMATION

In this part, the performance of the proposed MPSO algorithm, is evaluated as a comparison with the performances of the MP-based method [22] and FrFT-based method [27].




(a) (b)

**FIGURE 2.** Property of ZCZ sequence. (a) auto-correlation (b) cross-correlation.

**TABLE 2.** Parameters of MPSO.

| Parameter | value |
|---|---|
| cognitive scale parameter ($c_1$) | 2 |
| social scale parameter ($c_2$) | 2 |
| inertia weight ($\omega_k$) | 1 |
| two-dimensional maximum velocity ($v_{\max}$) | (1.02,512 samples) |
| maximum iterations ($k_{\max}$) | 30 |
| population of particles ($p$) | 200 |
| threshold 1 ($thr1$) | 0.1 |
| threshold 2 ($thr2$) | 0.4 |
| delay difference threshold ($\Delta_{peak}$) | 30 samples |

For MP-based method, we construct a signal dictionary correspond to delay-scale spreading function (DSSF) [27], the detail information about DSSF can be seen in Appendix B. The dictionary is composed of atoms which are scale-delay versions of the transmitted LFM signal. The atoms are sampled uniformly on scale factor and the sampling interval $\Delta\alpha$ equals 0.001 [27], and the time delay difference of two atoms with the same scale factor is one sample.

The proposed MPSO algorithm and FrFT-based method both apply the path-based channel model, while the MP-based method applies the DSSF's virtual representation model [27]. Due to the model difference, we modify the output of MPSO and FrFT-based method into the DSSF matrix $H_{M\times N}$, in order to compare their performance fairly. The $(m, n)th$ element is $H[m, n] = \alpha_m^{1/2}\eta_{m,n}$, combing the normalization factor. The scale factors, time delays, and amplitudes can be modified by [27]:

$$\begin{cases} \alpha_m = 1 + (m-1)/1000 \\ \tau_n = (n-1)/f_s \\ A_{m,n} = H[m,n] = \alpha_m^{1/2}\eta_{m,n} \end{cases}, \quad \begin{matrix} for\ m = 1,\ldots,M \\ n = 1,\ldots,N \end{matrix} \tag{39}$$

where $\eta_{m,n}$ is the sampling value of the $(m, n)th$ grid of the discretized DSSF [27] and $f_s$ is the sampling rate.

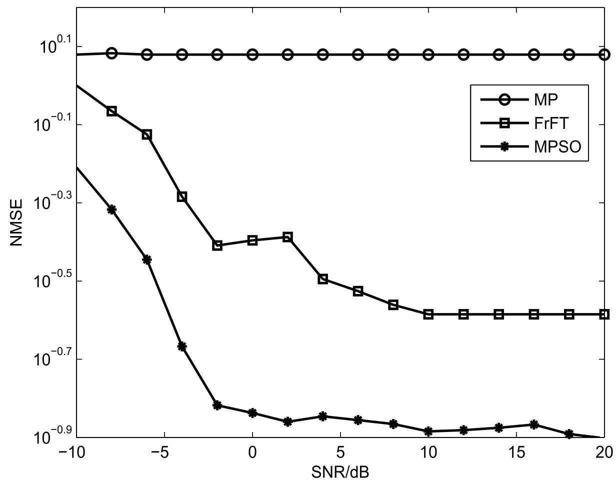



**FIGURE 3.** NMSEs of the DSSF estimates versus SNR.

### 1) PERFORMANCE COMPARISON OF THE DSSF ESTIMATIONS

We adopt the normalized mean squared error (NMSE) in the following as the evaluation indicator of the estimation accuracy,

$$NMSE_{DSSF} = \frac{\sum_m \sum_n |\hat{H}[m,n] - H[m,n]|^2}{\sum_m \sum_n |H[m,n]|^2} \tag{40}$$

where $\hat{H}[m, n] = \hat{\alpha}_m^{1/2}\hat{\eta}_{m,n}$ denotes the discrete DSSF estimate for the simulated algorithms.

The NMSEs of the estimated DSSF using MP, FrFT methods and MPSO algorithm versus SNR are drawn in Fig.3.

It can be seen that the estimation accuracy of the proposed MPSO algorithm and the FrFT-based method are significantly better than the MP-based method. The MPSO algorithm is slightly better than FrFT-based method for low SNR, gaining about 4dB; and much better as SNR increases, that is,

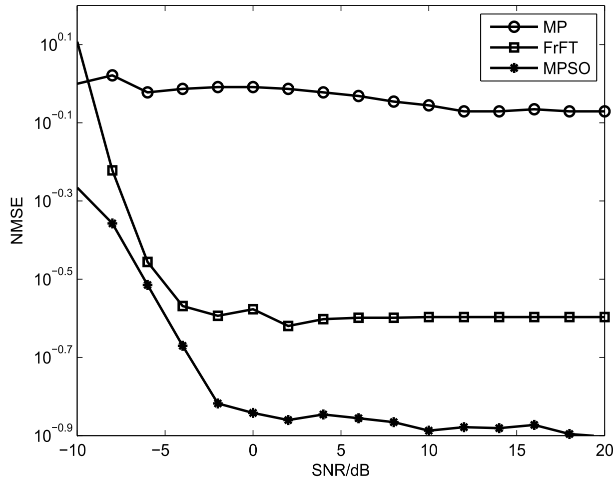



**FIGURE 4.** NMSEs of the PSP estimates versus SNR.

after the SNR exceeds −4dB, the gap is away from the FrFT method.

### 2) PERFORMANCE COMPARISON OF THE POWER SCALE PROFILE (PSP) ESTIMATIONS

Further, we compare the PSP performances of the MPSO algorithm and other methods. The PSP of the channel can be obtained by stacking up the delay dimension of the DSSF [27]. The NMSE of the PSP can be calculated by

$$NMSE_{PSP} = \frac{\sum_m |\sum_n \hat{H}[m,n] - \sum_n H[m,n]|^2}{\sum_m |\sum_n H[m,n]|^2} \quad (41)$$

The numerical simulation results are depicted in Fig.4, the MPSO algorithm performs much better compared with the MP-based method, and outperforms the FrFT-based method, especially after the SNR exceeds −2dB. However, when SNR is in −8∼-4dB, performances of the two methods are close, MPSO performs only a little better than FrFT method. Comparing to Fig.3, we find that both MP method and FrFT method in low SNR perform much better in NMSE of the PSP than DSSF estimates while MPSO not. So we speculate that LFM signal has a poor performance on time synchronization [2], thus cannot estimate delay accurately, so it performs better when stacking up the delay dimension. Therefore, we turn to evaluate the performance of MPSO in the NMSE of scale factor and the error of delay in the following part.

### 3) PERFORMANCE COMPARISON OF THE SCALE FACTOR ESTIMATIONS

To compare the estimation accuracy of the scale factors, we investigate the NMSEs of the scale factor estimates as the following formula:

$$NMSE_{scale} = \frac{\sum_{l=1}^{L} |\hat{\alpha}_l - \alpha_l|^2}{\sum_{l=1}^{L} |\alpha_l|^2} \quad (42)$$

and show the results in Fig.5. The MPSO algorithm outperforms the other two methods significantly, and even at −10dB, the MPSO algorithm can estimate the scale factor as accurate as the FrFT-based method in high SNR.

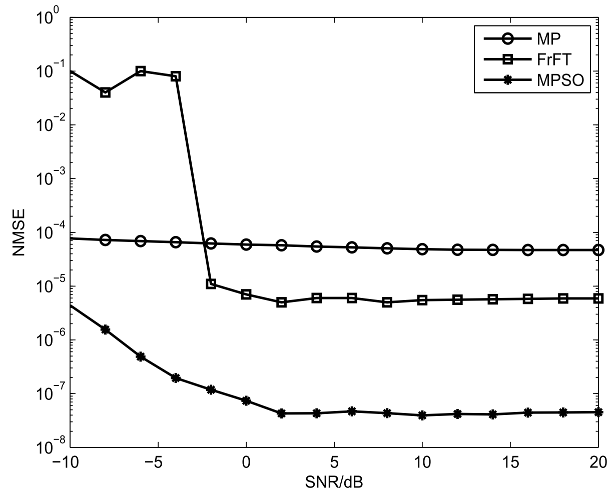



**FIGURE 5.** NMSEs of the scale factor estimates versus SNR.

### 4) PERFORMANCE COMPARISON OF THE TIME DELAY ESTIMATIONS

Time delay is one of the channel parameters we need to estimate, for it carries important channel information, for example, the propagation distance between the transmitter and the receiver as well as the path intensity. The estimation accuracy can be evaluated by error of delay estimate:

$$Error_{delay} = \frac{1}{L}\sum_{l=1}^{L} |\hat{\tau}_l - \tau_l| \quad (43)$$

where $L$ is the number of the dominant paths.

As a comparison, the performance of the MP-based and FrFT-based methods are also evaluated. For the training sequences of the MP-based method, the LFM sequence, PN sequence and ZCZ sequence are simulated respectively. The estimate error is averaged over the results of 500 trials for each method. It can be seen that the proposed MPSO method outperforms the others from the error results, which are drawn in Fig.6. Specifically, PN-MP, ZCZ-MP, FrFT and MPSO methods perform better with the increase of SNR, nevertheless, LFM-MP method keeps fluctuating around the error of 2.6 samples. When the SNR exceeds 4dB, PN-MP, ZCZ-MP and MPSO methods all outperform the two LFM-based method: LFM-MP and FrFT. It strongly suggests that LFM signal has poor time resolution. ZCZ-MP performs better than PN-MP, especially in low SNR, which indicates that ZCZ sequence has better correlation properties than PN sequence. So utilizing the good property of ZCZ sequence, the proposed MPSO algorithm can achieve a satisfactory performance after −5dB as the estimate error is approximately zero.

### 5) PERFORMANCE ANALYSIS

For MP-based method, the performance has no improvement as the SNR increases, i.e., its NMSEs or estimate error show no obvious downtrend in Figs 3,4,5,6. Such result owes to two reasons, one is the poor time resolution of the LFM signal in the scale-delay domain, which results in an inaccurate

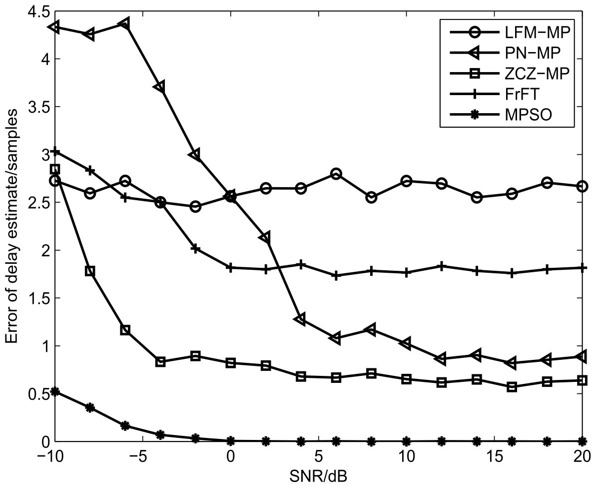



**FIGURE 6.** Errors of delay estimate versus SNR.

estimate of the time delay. And inaccurate delay estimate also leads to an inaccurate scale factor estimate. The other is that MP-based method uses a dictionary which composed of scale-delay versions of the transmitted LFM signal. So if one scale-delay version is not included in the dictionary, the method can only use other versions to approximate it, thus the estimation error cannot be eliminated by increasing the SNR.

For FrFT-based method, the performance is not satisfactory, especially in low SNR, i.e., the NMSE of the scale factor estimate is worse than MP method. One of the reason is the same as MP method as it also involves LFM signal as preamble. Another reason may be that it separates the multicomponents from the overlapped LFM signals during iterations. So if the estimated parameters of one iteration is inaccurate, the latter iterations will be influenced.

For MPSO algorithm, firstly, it adopts ZCZ sequence as preamble. As we mentioned above, ZCZ sequence has excellent correlation properties, which can resist multipath interference without the need of multipath separation like MP and FrFT methods do. Thus, it is in favor of delay estimation. Secondly, like many other evolutionary computation algorithms, MPSO algorithm can dynamically adjust particle's velocity according to *lbest* and *pbest*. Thus it can search a much larger portion of the problem space, and get more accurate positions than methods like MP, which uses a fixed dictionary.

### C. COMPLEXITY ANALYSIS

Another considerable issue is the complexity of the channel estimation algorithm. For MP-based method, FrFT-based method and the proposed MPSO algorithm, the computation mainly includes two parts: 1) the calculation of the inner products between the received signal and the local delay-scale version. 2) The iterations in which the algorithm distinguishes the dominant paths and estimates their parameters.

1) Complexity of MP-based method: Let $K_L$ denotes the average samples of the local delay-scale version of LFM signal. $N = N_\tau N_\alpha$ is the total number of delay-scale versions, i.e., atoms in the dictionary. In each iteration, the inner products between the received signal and atoms in the dictionary require $\rho_1 = NK_L$ complex multiplications and $\rho_2 = N(K_L - 1)$ additions. Therefore, the total operation counts for $R_{MP}$ iterations are of the order of $O(R_{MP}NK_L)$.
2) Complexity of FrFT-based method: According to Algorithm 2 in [27], at each iteration, the major computation is spent on FrFT scanning, i.e., the step 1 and step 4 in Algorithm 2, whose calculation is $O(N_{FrFT}K_L \log K_L)$, where $K_L$ is the samples of the transmitted LFM signal, $N_{FrFT}$ is the number of total FrFT times in the scanning and approximately equals to 77 in [27]. In step 2∼5, a sub-iteration is included for the optimal fractional order adjusting according to the estimated time delay. Specifically, in step 3, the calculation of searching for delay is $O({K_L}^2)$, and in step 4, rescanning the FrFT requires the calculation of $O(N_{FrFT}K_L \log K_L)$. Totally, four order adjusting loops are required for the sub-iteration. Therefore, the total operation counts for $R_{FrFT}$ iterations are of the order of $O(5R_{FrFT}N_{FrFT}K_L \log K_L + 4R_{FrFT}{K_L}^2)$.
3) Complexity of MPSO algorithm: We assume there are $P$ particles and maximum number of iteration times is $R_{MPSO}$. For MPSO algorithm, the computation is mainly determined by calculating fitness value for each particle. Fitness value is defined as the inner products between the received signal and delay-scale version of original ZCZ sequence. At the initialization period, the computation for evaluating initial fitness values is $O(PK_Z)$, $K_Z$ is the length of the ZCZ sequence. Then at the optimization period, the main computation is in step 4∼10, of the order of $O(PK_Z)$. Thus, the overall computation is of the order of $O(PK_Z + R_{MPSO}PK_Z)$.
4) Complexity comparison:
Note that in both MP and FrFT methods, the maximum number of iterations is determined by path numbers. So $R_{MP}$ and $R_{FrFT}$ approximately equal to path numbers, 8, in this paper. And we suppose the scale factor $\alpha \in [1, 1.02]$, with the sampling interval $\Delta\alpha = 0.001$, thus $N_\alpha = 21$. In addition, we assume signals from different paths arrive at the receiver within one signal duration $T$. Since we adopt $\Delta\tau = \frac{1}{f_s}$, $f_s$ is the sampling rate, then $N_\tau = \frac{T}{\Delta\tau}$. For MP and FrFT method, $N_\tau = K_L = 4000$, refer to the simulation part in [27]. And for MPSO method, we set $P = 200$ and $R_{MPSO} = 30$ in the simulation, and $K_Z = 512$. In conclusion, use the above numerical values, we list the computations of these methods in Table 3. It shows that the complexity of the proposed MPSO algorithm is far less than that of the other two methods.

**TABLE 3.** Complexity comparison.

| Algorithm | Computation | Numerical value |
|---|---|---|
| MP | $O(R_{MP}NK_L)$ | $6.72 \times 10^8$ |
| FrFT | $O(5R_{FrFT}N_{FrFT}K_L \log K_L + 4R_{FrFT}{K_L}^2)$ | $5.56 \times 10^8$ |
| MPSO | $O(PK_Z + R_{MPSO}PK_Z)$ | $3.17 \times 10^6$ |

## VI. CONCLUSION

In this paper, we model the UWA channels as MSML channels which can be parameterized in a path-wise manner. Signals from different paths can be distinguished by the triplets of Doppler scale factors, time delays and amplitudes. And by exploiting the sparsity of UWA channels, only the dominant paths' parameters need to be estimated. Based on this, we propose MPSO algorithm for parameter estimation of MSML channels. The main advantage of the proposed algorithm is that it can search a much larger portion of the problem space and get more accurate estimation than other existing methods, like MP-based method and FrFT-based method. Furthermore, the ZCZ sequence is transmitted as the training signal and its good correlation properties are in favor of the time delay estimation. The performance gain of the MPSO algorithm is demonstrated through comparing the estimation accuracies of the DSSF, the PSP, the scale factor and the time delay with MP-based and FrFT-based methods. Simulation results show that the performance of the MPSO algorithm surpasses the other two methods.

## APPENDIX A
## THE FORMULA DEDUCTION OF RECEIVER PROCESSION

Performing down conversion and ZP-OFDM demodulation:

$$y_m = \frac{1}{T}\int_0^{T/a_l} \tilde{y}(t)e^{-j2\pi f_c t}e^{-j2\pi \frac{m}{T}t}dt \tag{44}$$

for the sake of simplicity, Plugging in $\tilde{y}(t)$ without $n(t)$ and $q(t)$:

$$\begin{aligned} y_m &= \sum_{l=1}^{L} A_l e^{j2\pi(f_c+\frac{k}{T})(-\tau_l)} \sum_{k=0}^{K-1} s[k] \\ &\quad \times \frac{1}{T}\int_0^{T/a_l} e^{j2\pi f_c(a_l-1)t}e^{j2\pi\frac{k}{T}a_l t}e^{-j2\pi\frac{m}{T}t}dt \\ &= \sum_{l=1}^{L} A_l e^{j2\pi(f_c+\frac{k}{T})(-\tau_l)} \sum_{k=0}^{K-1} s[k]\frac{1}{T}\int_0^{T/a_l} e^{j2\pi(a_l f_k - f_m)t}dt \\ &= \sum_{l=1}^{L} A_l e^{j2\pi(f_c+\frac{k}{T})(-\tau_l)} \sum_{k=0}^{K-1} s[k]\frac{1}{T}\frac{(e^{j2\pi(a_l f_k - f_m)T/a_l}-1)}{j2\pi(a_l f_k - f_m)} \end{aligned} \tag{45}$$

where

$$\begin{aligned} &\frac{1}{T}\frac{(e^{j2\pi(a_l f_k - f_m)T/a_l}-1)}{j2\pi(a_l f_k - f_m)} \\ &= \frac{1}{T}\frac{\cos(2\pi(a_l f_k - f_m)\frac{T}{a_l}) + j\sin(2\pi(a_l f_k - f_m)\frac{T}{a_l}) - 1}{j2\pi(a_l f_k - f_m)} \\ &= \frac{1}{T}(\frac{2\sin(\pi(a_l f_k - f_m)\frac{T}{a_l})\cos(\pi(a_l f_k - f_m)\frac{T}{a_l})}{j2\pi(a_l f_k - f_m)} \\ &\quad - \frac{2\sin^2(\pi(a_l f_k - f_m)\frac{T}{a_l})}{j2\pi(a_l f_k - f_m)}) \\ &= \frac{1}{T}\frac{\sin(\pi(a_l f_k - f_m)\frac{T}{a_l})}{\pi(a_l f_k - f_m)}(\cos(\pi(a_l f_k - f_m)\frac{T}{a_l}) \\ &\quad + j\sin(\pi(a_l f_k - f_m)\frac{T}{a_l})) \\ &= \frac{1}{a_l}\frac{\sin(\pi(a_l f_k - f_m)\frac{T}{a_l})}{\pi(a_l f_k - f_m)\frac{T}{a_l}}e^{j\pi(a_l f_k - f_m)\frac{T}{a_l}} \end{aligned} \tag{46}$$

let

$$\beta_{k,m}^{l} = (a_l f_k - f_m)/a_l = (k-m)\frac{1}{T} + \frac{(a_l-1)f_m}{a_l} \tag{47}$$

Therefore,

$$\begin{aligned} y_m &= \sum_{l=1}^{L}\frac{A_l}{a_l}\sum_{k=0}^{K-1} s[k]e^{-j2\pi(f_c+\frac{k}{T})\tau_l}\frac{\sin(\pi\beta_{k,m}^{l}T)}{\pi\beta_{k,m}^{l}T}e^{j\pi\beta_{k,m}^{l}T} \\ &= \sum_{l=1}^{L}\frac{A_l}{a_l}e^{-j2\pi f_c\tau_l}\sum_{k=0}^{K-1} s[k]e^{-j2\pi\frac{k}{T}\tau_l}\mathrm{sinc}(\beta_{k,m}^{l}T)e^{j\pi\beta_{k,m}^{l}T} \end{aligned} \tag{48}$$

## APPENDIX B
## DELAY-SCALE SPREADING FUNCTION

The delay-scale spreading function (DSSF) $h(\alpha, \tau)$, is a continuous function that takes the scaling factor $\alpha$ and time delay $\tau$ as variables [27]. At the receiver, the received signal $r(t)$ can be written as

$$r(t) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} h(\alpha,\tau)\alpha^{1/2}s(\alpha(t-\tau))d\tau d\alpha \tag{49}$$

where $\alpha^{1/2}$ is a normalization factor. This model reflects the fact that in wideband UWA communication, the received signal $r(t)$ can be represented by different scaled (by $\alpha$) and delayed (by $\tau$) versions of the transmitted signal, and each weighted by $\alpha^{1/2}h(\alpha, \tau)$.

The DSSF can be discretized through sampling at regular intervals on the delay-scale plane. To be specific, let $h(\alpha, \tau) = 0, \forall(\alpha, \tau) \notin [\alpha_{\min}, \alpha_{\max}] \times [0, \tau_{\max}]$, where $\alpha_{\min}, \alpha_{\max}$ denote the lower bound and upper bound of the scale factor changing and $\tau_{\max}$ denotes the maximum delay of the channel. The expression of the DSSF can be written as:

$$\tilde{h}(\alpha,\tau) = \sum_{m=1}^{M}\sum_{n=1}^{N}\eta_{m,n}\delta(\alpha-\alpha_m)\delta(\tau-\tau_n) \tag{50}$$

where $\alpha_m = \alpha_{mim} + m\Delta\alpha, \tau_n = n\Delta\tau, M = (\alpha_{\max} - \alpha_{\min})/\Delta\alpha, N = \tau_{\max}/\Delta\tau$, with $\Delta\alpha$ and $\Delta\tau$ denote the scale factor sampling interval and delay sampling interval, respectively. $\eta_{m,n}$ is the $(m, n)th$ sampling value of the discretized DSSF [27].

Substitute (50) into (49), we have

$$r(t) = \sum_{m}\sum_{n}\eta_{m,n}\alpha_m{}^{1/2}s(\alpha_m(t-\tau_n)) \tag{51}$$

## REFERENCES


[1] I. F. Akyildiz, D. Pompili, and T. Melodia, "Challenges for efficient communication in underwater acoustic sensor networks," *ACM SIGBED Rev.*, vol. 1, no. 2, pp. 3–8, Jul. 2004.

[2] S. F. Mason, C. R. Berger, S. Zhou, and P. Willett, "Detection, synchronization, and Doppler scale estimation with multicarrier waveforms in underwater acoustic communication," *IEEE J. Sel. Areas Commun.*, vol. 26, no. 9, pp. 1638–1649, Dec. 2008.

[3] A. C. Singer, J. K. Nelson, and S. S. Kozat, "Signal processing for underwater acoustic communications," *IEEE Commun. Mag.*, vol. 47, no. 1, pp. 90–96, Jan. 2009.

[4] S. Daoud and A. Ghrayeb, "Using resampling to combat Doppler scaling in UWA channels with single-carrier modulation and frequency-domain equalization," *IEEE Trans. Veh. Technol.*, vol. 65, no. 3, pp. 1261–1270, Mar. 2016.

[5] F. Qu, Z. Wang, L. Yang, and Z. Wu, "A journey toward modeling and resolving doppler in underwater acoustic communications," *IEEE Commun. Mag.*, vol. 54, no. 2, pp. 49–55, Feb. 2016.

[6] R. Diamant, "Closed form analysis of the normalized matched filter with a test case for detection of underwater acoustic signals," *IEEE Access*, vol. 4, pp. 8225–8235, 2016.

[7] T. H. Eggen, A. B. Baggeroer, and J. C. Preisig, "Communication over Doppler spread channels. Part I: Channel and receiver presentation," *IEEE J. Ocean. Eng.*, vol. 25, no. 1, pp. 62–71, Jan. 2000.

[8] D. B. Kilfoyle and A. B. Baggeroer, "The state of the art in underwater acoustic telemetry," *IEEE J. Ocean. Eng.*, vol. 25, no. 1, pp. 4–27, Jan. 2000.

[9] N. Iruthayanathan, K. S. Vishvaksenan, and V. Rajendran, "Performance of spread spectrum based multi-carrier system in underwater communication using transmitter pre-processing," *IEEE Access*, vol. 4, pp. 5128–5134, 2016.

[10] B. Li, S. Zhou, M. Stojanovic, L. Freitag, and P. Willett, "Multicarrier communication over underwater acoustic channels with nonuniform Doppler shifts," *IEEE J. Ocean. Eng.*, vol. 33, no. 2, pp. 198–209, Apr. 2008.

[11] Z. Chen, Y. Zheng, J. Wang, and J. Song, "Synchronization and Doppler scale estimation with dual PN padding TDS-OFDM for underwater acoustic communication," in *Proc. IEEE OCEANS Conf.*, San Diego, CA, USA, Sep. 2013, pp. 1–4.

[12] C. R. Berger, S. Zhou, J. C. Preisig, and P. Willett, "Sparse channel estimation for multicarrier underwater acoustic communication: From subspace methods to compressed sensing," *IEEE Trans. Signal Process.*, vol. 58, no. 3, pp. 1708–1721, Mar. 2010.

[13] B. Li, S. Zhou, M. Stojanovic, L. Freitag, and P. Willet, "Multicarrier underwater acoustic communications over fast-varying channels," *IEEE J. Ocean. Eng.*, vol. 33, no. 2, pp. 198–209, Apr. 2008.

[14] S. F. Mason, C. R. Berger, S. Zhou, K. R. Ball, L. Freitag, and P. Willett, "Receiver comparisons on an OFDM design for Doppler spread channels," in *Proc. IEEE OCEANS Conf.*, May 2009, pp. 2201–2208.

[15] T. Xu, Z. Tang, G. Leus, and U. Mitra, "Multi-rate block transmission over wideband multi-scale multi-lag channels," *IEEE Trans. Signal Process.*, vol. 61, no. 4, pp. 964–979, Feb. 2013.

[16] W. Li and J. C. Preisig, "Estimation of rapidly time-varying sparse channels," *IEEE J. Ocean. Eng.*, vol. 32, no. 4, pp. 927–939, Oct. 2007.

[17] M. Stojanovic, "OFDM for underwater acoustic communications: Adaptive synchronization and sparse channel estimation," in *Proc. Int. Conf. Acoust., Speech Signal Process.*, Las Vegas, NV, USA, Apr. 2008, pp. 5288–5291.

[18] B. S. Sharif, J. Neasham, O. R. Hinton, and A. E. Adams, "A computationally efficient Doppler compensation system for underwater acoustic communications," *IEEE J. Ocean. Eng.*, vol. 25, no. 1, pp. 52–61, Jan. 2000.

[19] K. Wang, S. Chen, C. Liu, Y. Liu, and Y. Xu, "Doppler estimation and timing synchronization of underwater acoustic communication based on hyperbolic frequency modulation signal," in *Proc. IEEE 12th Int. Conf. Netw., Sens. Control*, Taipei, Taiwan, Apr. 2015, pp. 75–80.

[20] M. Johnson, L. Freitag, and M. Stojanovic, "Improved Doppler tracking and correction for underwater acoustic communications," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Munich, Germany, Apr. 1997, pp. 575–578.

[21] S. F. Cotter and B. D. Rao, "Sparse channel estimation via matching pursuit with application to equalization," *IEEE Trans. Commun.*, vol. 50, no. 3, pp. 374–377, Mar. 2002.

[22] N. F. Josso *et al.*, "On the characterization of time-scale underwater acoustic signals using matching pursuit decomposition," in *Proc. IEEE OCEANS Conf.*, May 2009, pp. 1–6.

[23] F. Yu, D. Li, Q. Guo, Z. Wang, and W. Xiang, "Block-FFT based OMP for compressed channel estimation in underwater acoustic communications," *IEEE Commun. Lett.*, vol. 19, no. 11, pp. 1937–1940, Nov. 2015.

[24] F. Qu, X. Nie, and W. Xu, "A two-stage approach for the estimation of doubly spread acoustic channels," *IEEE J. Ocean. Eng.*, vol. 40, no. 1, pp. 131–143, Jan. 2015.

[25] P. H. Leong, T. D. Abhayapala, and T. A. Lamahewa, "Multiple target localization using wideband echo chirp signals," *IEEE Trans. Signal Process.*, vol. 61, no. 16, pp. 4077–4089, Aug. 2013.

[26] L. Zheng and D. Shi, "Maximum amplitude method for estimating compact fractional Fourier domain," *IEEE Signal Process. Lett.*, vol. 17, no. 3, pp. 293–296, Mar. 2010.

[27] Y. Zhao, H. Yu, G. Wei, F. Ji, and F. Chen, "Parameter estimation of wideband underwater acoustic multipath channels based on fractional Fourier transform," *IEEE Trans. Signal Process.*, vol. 64, no. 20, pp. 5396–5408, Oct. 2016.

[28] R. C. Eberhart and Y. Shi, "Particle swarm optimization: Developments, applications and resources," in *Proc. Congr. Evol. Comput.*, Seoul, South Korea, May 2001, pp. 81–86.

[29] Y. Wang, S. He, Y. Sun, Q. Xu, H. Wang, and L. Yang, "Joint timing synchronization and channel estimation based on ZCZ sequence set in SC-MIMO-FDE system," *EURASIP J. Wireless Commun. Netw.*, vol. 49, p. 49, Dec. 2016.

[30] P. Z. Fan, N. Suehiro, N. Kuroyanagi, and X. M. Deng, "Class of binary sequences with zero correlation zone," *Electron. Lett.*, vol. 35, no. 10, pp. 777–779, May 1999.

[31] P. Fan, "Spreading sequence design and theoretical limits for quasisynchronous CDMA systems," *EURASIP J. Wireless Commun. Netw.*, vol. 1, pp. 19–31, Aug. 2004.

[32] S.-A. Yang and J. Wu, "Optimal binary training sequence design for multiple-antenna systems over dispersive fading channels," *IEEE Trans. Veh. Technol.*, vol. 51, no. 5, pp. 1271–1276, Sep. 2002.

[33] P. Fan and W. H. Mow, "On optimal training sequence design for multiple-antenna systems over dispersive fading channels and its extensions," *IEEE Trans. Veh. Technol.*, vol. 53, no. 5, pp. 1623–1626, Sep. 2004.

[34] R. Zhang, X. Cheng, M. Ma, and B. Jiao, "Interference-avoidance pilot design using ZCZ sequences for multi-cell MIMO-OFDM systems," in *Proc. IEEE Global Commun. Conf.*, Anaheim, CA, USA, Dec. 2012, pp. 5056–5061.

[35] H. Torii, M. Nakamura, and N. Suehiro, "A new class of zero-correlation zone sequences," *IEEE Trans. Inf. Theory*, vol. 50, no. 3, pp. 559–565, Mar. 2004.

[36] J. Kennedy and R. C. Eberhart, "Particle swarm optimization," in *Proc. Int. Conf. Neural Netw.*, Perth, WA, Australia, 1995, pp. 1942–1948.


**XING ZHANG** received the B.S. degree from Southeast University, China, in 2015, where he is currently pursuing the Ph.D. degree. She is major in information and communication engineering and interested in synchronization, Doppler scale estimation, and channel estimation in underwater acoustic communications.

**KANG SONG** received the B.S. degree from Anhui University, China, in 2009, and the Ph.D. degree in information and communication engineering from Southeast University, China, in 2016. Since 2016, he has been a Faculty Member with the School of Electronic and Information Engineering, Qingdao University. His current research interests include network coding, cooperative communications, and heterogeneous networks.

**CHUNGUO LI** (SM'–) received the bachelor's degree in wireless communications from Shandong University in 2005, and the Ph.D. degree in wireless communications from Southeast University in 2010. In 2010, he joined the Faculty of Southeast University, Nanjing, where he has been an Associate Professor since 2012 and also has been the Supervisor of Ph.D. candidate since 2016. From 2012 to 2013, he was the Post-Doctoral researcher with Concordia University, Montreal, Canada. Since 2013, he has been with the DSL laboratory, supervised by Prof. J. M. Cioffi. His research interests are in the 5G cellular transmission, underwater communications, green communications, and next generation of WiFi. He is currently the Area Editor of the *Elsevier AEU-International Journal of Electronics and Communications*, the Associate Editor of the *Circuits, Systems and Signal Processing*, the Editor of the *KSII Transactions on Internet and Information Systems* and has served for many IEEE conferences, including the IEEE 16th International Symposium on Communications and Information Technologies as the Track Chair of Wireless Communications, the International Conference on Communications, the International Conference on Acoustics, Speech and Signal Processing as the TPC Member. He is the Reviewer for many IEEE Journals. He is the Senior Member of the Chinese Institute of Electronics. He is a recipient of the Southeast University Excellent Young Professor Award in 2015, the Science and Technology Progress Award of the National Education Ministry of China in 2014, the Excellent Visiting Associate Professor at Stanford in 2014, the Excellent Foreign Postdoc Award of Canada in 2012, the Best Ph.D. Thesis Award of Southeast University in 2010, and several conference best paper awards.

**LUXI YANG** (M'96) received the M.S. and Ph.D. degrees in electrical engineering from the Southeast University, Nanjing, China, in 1990 and 1993, respectively. Since 1993, he has been with the Department of Radio Engineering, Southeast University, where he is currently a Professor of Information Systems and Communications, and the Director of the Digital Signal Processing Division. His current research interests include signal processing for wireless communications, MIMO communications, cooperative relaying systems, and statistical signal processing. He has authored or co-authored two published books and over 100 journal papers, and holds 30 patents. He received the first and second class prizes of science and technology progress awards of the state education ministry of China in 1998, 2002, and 2014. He is currently a member of the Signal Processing Committee of the Chinese Institute of Electronics.