Online Hop Timing Detection and Frequency Estimation of Multiple FH Signals

Zhi-Chao Sha, Zhang-Meng Liu, Zhi-Tao Huang, and Yi-Yu Zhou

This paper addresses the problem of online hop timing detection and frequency estimation of multiple frequency-hopping (FH) signals with antenna arrays. The problem is deemed as a dynamic one, as no information about the hop timing, pattern, or rate is known in advance, and the hop rate may change during the observation time. The technique of particle filtering is introduced to solve this dynamic problem, and real-time frequency and direction of arrival estimates of the FH signals can be obtained directly, while the hop timing is detected online according to the temporal autoregressive moving average process. The problem of network sorting is also addressed in this paper. Numerical examples are carried out to show the performance of the proposed method.

Keywords: Array signal processing, frequency hopping, FH, frequency estimation, hop timing detection, network sorting.

Manuscript received Nov. 16, 2012; revised Jan. 11, 2013; accepted Feb. 2, 2013.

This research was supported by the National Natural Science Foundation of China (No. 61072120), and the Program for New Century Excellent Talents in University of China (NCET).

Zhi-Chao Sha (phone: +86 073184573489, shazhichao_163@163.com), Zheng-Meng Liu (zm_liur@sohu.com), Zhi-Tao Huang (taldcn@yahoo.com..cn), and Yi-Yu Zhou (zhouyiyu@shou.com) are with the College of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China.

http://dx.doi.org/10.4218/etrij.13.0112.0787

I. Introduction

Frequency hopping (FH) is one of the prevailing spread spectrum technologies in communications owing to its low probability of detection and interception, and vast efforts have been made to study the parameter estimation methods of such signals. Single-antenna-based methods and multiple-antenna-based methods exist that can address this problem.

The single-antenna-based methods exploit the temporal properties of the FH signals to estimate their parameters, such as hop rate and frequency. Chung and Polydoros proposed the methods known as multiple-hop observation autocorrelation and single-hop observation autocorrelation to estimate the hop rate and hop timing [1], [2]. The methods in [2] were further developed by Janani and others in [3] to jointly estimate the hop rate and signal power. Barbarossa and Scaglione then introduced the pseudo Wigner-Ville distribution in [4] to estimate the hop period, hop instant, and frequency. The technique of matching pursuit [5] was brought in for blind parameter estimation of FH signals by Fan and others in [6]. Ko and others focused on the estimation of the hop instant with the maximum likelihood method for network synchronization [7]. Angelosante and others focused on the estimation of the hop instant with the sparse linear regression method [8] and obtained a more satisfactory performance than when using the time-frequency distribution method.

Although the above-mentioned methods are quite different in principle, they can only make use of the diversity of FH signal hop times to sort FH networks. So, these methods can only be used to sort asynchronous networks whose hop times have different rules. To deal with the problem of parameter estimation of combined synchronous or asynchronous FH signal and network sorting, researchers have resorted to the multiple-antenna systems. Liu and others were the first researchers to use antenna arrays for multiple FH signal parameter estimation [9]-[14]. In [9], they first separated the FH signals via spatial filtering and then used the dynamic programming method to estimate the hop times and frequencies from the separated data. This method works well only when the hopping frequency contributes little to the carrier frequency; thus, it does not adapt to shortwave FH signals due to their wide hop bandwidth [15]. The researchers in [10]-[13] studied the parameter estimation of multiple FH signals in expanded cases, such as multipath, two-dimensional arrays, frequency collision, receiver bandwidth mismatches, and so on. Liu's work on these methods was completed in [14].

A common shortcoming shared by the above-mentioned single- and multiple-antenna-based methods is that they need sufficient snapshots; therefore, their applicability in online information extraction and interference suppression is vague. In [16], Liu and others proposed a method based on a temporal autoregressive moving average (ARMA) model to detect the frequency hops upon occurrence and track the frequency hopping online. However, because the method is a multiple-antenna-based method that does not consider the direction of arrival (DOA) of the signals, the performance is unsatisfactory. This paper deems the problem of obtaining real-time parameter estimates of multiple FH signals as a dynamic one and introduces particle filters to solve it.

In our method, we use the particle filters [17] to obtain the array responding vectors of the incident signals first and then recover the signal waveforms to estimate the signal frequencies. After that, the responding vectors and signal frequency estimates are combined to get the signal directions. To realize online hop timing detection, the ARMA-model-based method is used to detect frequency hopping online. Then, the sorting of the asynchronous network is implemented by exploiting the frequency continuity of the hop-free signals at each hop instant, and that of the synchronous network is implemented according to the distinguishable and inactive signal directions.

The main contribution of this paper is proposing an algorithm to detect hop timing and estimate the frequencies of multiple FH signals with antenna arrays, which is based on combining the particle filter [17] with the ARMA model [16]. It should be noted that some of the ideas regarding the particle filter come from Larocque and others [17], but necessary modifications are made regarding the special problem addressed in this paper, and some brief repetitions are introduced only for integrality of the method. By introducing the particle filter algorithm, the proposed method solves the problem of online hop timing detection and frequency estimation of multiple FH signals with better effectiveness than the algorithm in [16] for asynchronous networks. Moreover, the proposed method is capable of sorting synchronous networks, whereas the ARMA model method is not.

This paper is organized as follows. Section II presents a review of the array output model in the case that more than one FH signal impinges on an array. Section III introduces the temporal ARMA model at each dwell for frequency hopping detection. Section IV presents the exploitation of particle filters to obtain online array responding vectors and signal frequency estimates. The processes of parameter estimation and network sorting with sketch maps are concluded in section V. Section VI contains numerical examples to examine the performance of the proposed method, and conclusions are given in section VII.

II. Problem Formulation

The uniform linear array (ULA) is considered for notation convenience, but our method is capable of adapting to arrays with random geometry.

Suppose that K FH signals impinge on an M-element ULA simultaneously, with K assumed to be known and $M>K$. The inter-element spacing of the ULA is D, and the incident directions of the K signals are $\mathbf{\Theta}=[\theta_1,\cdots,\theta_K]$, while the signal frequencies during the current dwell are $\mathbf{F}=[f_1,\cdots,f_K]$, and the sampling interval is T_s.

If $\varphi_k=2\pi f_k T_s$ and $\phi_k=2\pi f_k D\cos\theta_k/C$ are defined, wherein C is the velocity of light, then the samples collected at time t can be denoted as follows [9]:

$$\mathbf{x}_t=\sum_{k=1}^{K}\mathbf{a}_k\rho_k e^{j(t-1)\varphi_k}+\mathbf{n}_t=\mathbf{A}\mathbf{s}_t+\mathbf{n}_t, \qquad (1)$$

where $\mathbf{A}=[\mathbf{a}_1,\cdots,\mathbf{a}_K]$, $\mathbf{a}_k=\left[1,\cdots,e^{j(M-1)\phi_k}\right]^{\mathrm{T}}$, $\mathbf{s}_t=\left[\rho_1 e^{j(t-1)\varphi_1},\cdots,\rho_K e^{j(t-1)\varphi_K}\right]^{\mathrm{T}}$ is defined as the signal waveform vector at time t, and where $\rho_k\,(k=1,\ldots,K)$ comprises the amplitudes and initial phases of the k-th signal and $\mathbf{n}_t$ is the additive Gaussian noise with zero mean and $\sigma_n^2\mathbf{I}_M$ variance.

If a given signal hops frequencies, the array output will no longer satisfy (1). This paper seeks to detect those hop instants, obtain frequency estimates in a timely fashion once a frequency hop occurs, and obtain the signal DOA whenever desired.

III. Online Hop Timing Detection

This section first introduces a temporal ARMA model for the array output during each dwell and then uses it to detect the frequency hopping by checking the prediction error.

1. Temporal ARMA Model

The temporal snapshots of K overlapped noisy complex sinusoids complies with the following ARMA model of order (K+1, K+1) [16]:

$$\sum_{i=0}^{K} c_i \mathbf{x}_{t+i} = \sum_{i=0}^{K} c_i \mathbf{n}_{t+i}, \quad (2)$$

where $c_K = 1$, and $c_0, c_1, \cdots, c_{K-1}$ can be obtained from the following polynomial [16]-[19]:

$$f(\alpha) = \prod_{k=1}^{K} \left(\alpha - e^{j\varphi_k}\right) = c_K \alpha^K + \cdots + c_1 \alpha + c_0. \quad (3)$$

The coefficients $\{c_k\}$ depend directly on the signal frequencies.

2. Frequency Hopping Detection

If the coefficients of the ARMA model established above are available and are used to eliminate the signal components in $K+1$ successive samplings, the residual noise complies with the following Gaussian distribution:

$$\sum_{i=0}^{K} c_i \mathbf{x}_{t+i} = \sum_{i=0}^{K} c_i \mathbf{n}_{t+i} \sim \mathbf{N}\left(\mathbf{0}, \left(\sum_{i=0}^{K} |c_i|^2\right) \sigma_n^2 \mathbf{I}_M\right). \quad (4)$$

Predict each hop instant, indexed by t_h, with the former K observations, according to the ARMA model, as follows:

$$\hat{\mathbf{x}}_{t_h} = -\sum_{i=0}^{K-1} c_i \mathbf{x}_{t_h - K + i}, \quad (5)$$

However, if a signal frequency hop does not occur at the moment predicted, the deviation between the actual output and its prediction has zero mean and a variance of $\left(\sum_{i=0}^{K} |c_i|^2\right) \sigma_n^2 \mathbf{I}_M$, that is,

$$\mathbf{x}_{t_h} - \hat{\mathbf{x}}_{t_h} \sim \mathbf{N}\left(\mathbf{0}, \left(\sum_{i=0}^{K} |c_i|^2\right) \sigma_n^2 \mathbf{I}_M\right). \quad (6)$$

Yet, if one or more signals hop frequencies at the time predicted, the prediction error is much more significant than that shown in (6). We detect the possible hops according to the significance of the prediction error via hypothesis testing, according to

$$\left\| \mathbf{x}_{t_h} - \hat{\mathbf{x}}_{t_h} \right\|_2^2 \underset{\mathrm{H}_0}{\overset{\mathrm{H}_1}{\gtrless}} \zeta, \quad (7)$$

where H_1 stands for the hypothesis "frequency hopping happens" and H_0 stands for the hypothesis "no frequency hopping happens." Symbol ζ represents the judgment threshold, and the way ζ is selected is provided in [16].

IV. Online Frequency Estimation and Network Sorting

The FH signals are stationary during each dwell, but as we do not know when each dwell begins and how long it lasts, we cannot use linear methods to estimate frequencies. In the context of online frequency hopping estimation, we deem the analysis of the locally stationary model as a dynamic problem, and the technique of particle filtering is introduced to perform such analysis.

As the FH signals might hop frequencies and the DOA is unknown, only the array responding vectors can be directly extracted from the array output, within which the signal frequencies and DOA are coupled. Therefore, during the process of parameter estimation, the inter-element phase shift and the signal frequency, that is, ϕ_k and f_k instead of θ_k and f_k, is used to describe the spatial and temporal character of the incident signals, and ϕ_k is considered the frequency-direction product (FDP) for notation convenience. First, we estimate the FDP-dependent responding vectors and then obtain the signal frequencies from recovered waveforms. The signal DOA is calculated using the FDP and frequency estimates, if desired. As the FDP does not cast any restriction to the array geometry, we believe that the new method adapts to arrays of various shapes, as is claimed at the beginning of section II.

1. FDP Estimation

The estimation of the signal FDP via particle filtering consists of two steps: initialization and updating. During the initialization step, the weights of all K-dimensional particles are set to $1/Q$, where Q is the number of particles, and the value of each particle element is set according to the spatial power distribution of the first array snapshot, that is,

$$g(\phi) \propto \sum_{l=0}^{M-1} p_l \Gamma_{[2\pi l/M, 2\pi(l+1)/M)}(\phi), \quad (8)$$

where p_l is the power of the first array snapshot at the digital frequency of $2\pi l/M$[1)] and $\Gamma_{[2\pi l/M, 2\pi(l+1)/M)}(\phi)$ is the indicative function, that is,

$$\Gamma_{[2\pi l/M, 2\pi(l+1)/M)}(\phi) = \begin{cases} 1, & \phi \in [2\pi l/M, 2\pi(l+1)/M), \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

We organize the KQ elements in ascending order and divide them into K groups of equal size. Finally, Q K-dimensional particles of $\mathbf{\Phi}_{q=1}^{Q} = \left\{\phi_q^{(1)}, \cdots, \phi_q^{(K)}\right\}_{q=1}^{Q}$ are generated, with each

1) For notational convenience, the non-ambiguous frequency scope is shifted from $[-\pi, \pi)$ to $[0, 2\pi)$.

particle randomly selecting an element from each group.

Because more data is received before any frequency hopping happens, those particles should be updated according to the posterior distribution of that data. Suppose that t_h array samplings, that is $\mathbf{x}_{1:t_h}$, have been collected before the next occurrence of frequency hopping. Due to the Gaussian distribution of the additive noise, each array snapshot complies with a Gaussian distribution, as follows:

$$\mathbf{x}_t \sim \mathbf{N}\left(\mathbf{A}\mathbf{s}_t, \sigma_n^2 \mathbf{I}_M\right), \qquad t = 1, \cdots, t_h, \tag{10}$$

where $N(\boldsymbol{\Xi}, \boldsymbol{\Sigma})$ stands for the Gaussian distribution with $\boldsymbol{\Xi}$ mean and $\boldsymbol{\Sigma}$ variance.

To facilitate the implementation of the particle filter, we add more distribution assumptions to the array output model. Those assumptions are mostly non-informative so that our subjective assumption does not force the method to deviate from practical applications.

The signal waveform is assumed to follow the maximum entropy Gaussian distribution with zero mean [17], [20], that is,

$$\mathbf{s}_t \sim \mathbf{N}\left(0, \sigma_n^2 \delta^2 \left(\mathbf{A}^{\mathrm{H}}\mathbf{A}\right)^{-1}\right), \quad t = 1, \cdots, t_h \tag{11}$$

where δ^2 is the signal-to-noise ratio (SNR). The signal FDP and noise variance follow uniform and inverted Gamma distributions with parameters $[-\pi, \pi)$ and (β, γ), respectively, that is,

$$\boldsymbol{\Phi} \sim \mathbf{U}^K[-\pi, \pi), \tag{12}$$

$$\sigma_n^2 \sim \mathbf{IG}(\beta, \gamma). \tag{13}$$

Combining (10) through (13), the posterior distribution of the t_h array outputs can be derived according to the Bayesian probability theorem, as follows:

$$\begin{aligned} & g\left(\phi_{1:K}, \mathbf{s}_{1:t_h}, \sigma_n^2 \middle| \mathbf{x}_{1:t_h}\right) \\ & \propto p\left(\mathbf{x}_{1:t_h} \middle| \phi_{1:K}, \mathbf{s}_{1:t_h}, \sigma_n^2\right) p\left(\phi_{1:K}\right) p\left(\mathbf{s}_{1:t_h}\right) p\left(\sigma_n^2\right) \\ & = \left(\pi\sigma_n^2\right)^{-(M+K)t_h} (2\pi)^{-K} \left(\sigma_n^2\right)^{-(\beta+1)} \left(\delta^{-2}\right)^{Kt_h} \left|\mathbf{A}^{\mathrm{H}}\mathbf{A}\right|^N \\ & \quad \cdot \exp\left\{-\frac{1}{\sigma_n^2}\left[\gamma + \sum_{t=1}^{t_h}\left(\left(1+\delta^{-2}\right)\mathbf{A}_s + \Delta_t\right)\right]\right\}, \end{aligned} \tag{14}$$

where

$$\mathbf{A}_s = \left(\mathbf{s}_t - \mathbf{m}_t\right)^{\mathrm{H}} \mathbf{A}^{\mathrm{H}}\mathbf{A}\left(\mathbf{s}_t - \mathbf{m}_t\right), \tag{15}$$

$$\mathbf{m}_t = \left(1+\delta^{-2}\right)^{-1} \left(\mathbf{A}^{\mathrm{H}}\mathbf{A}\right)^{-1} \mathbf{A}^{\mathrm{H}}\mathbf{x}_t, \tag{16}$$

$$\Delta_t = \mathbf{x}_t^{\mathrm{H}}\left(\mathbf{I}_M - \left(1+\delta^{-2}\right)^{-1} \mathbf{A}\left(\mathbf{A}^{\mathrm{H}}\mathbf{A}\right)^{-1}\mathbf{A}^{\mathrm{H}}\right)\mathbf{x}_t, \tag{17}$$

and the $\boldsymbol{\Phi}$ in $\mathbf{A}(\boldsymbol{\Phi})$ is left out for brevity, without causing any confusion.

It is obvious in (14) that the posterior distribution is a normal distribution of $\mathbf{s}_{1:t_h}$ and an inverted Gamma distribution of σ_n^2. Integrating the distribution function according to $\mathbf{s}_{1:t_h}$ and σ_n^2 yields the posterior distribution of the array outputs:

$$g\left(\phi_{1:K} \middle| \mathbf{x}_{1:t_h}\right) \propto \left(\gamma + \sum_{t=1}^{N} \Delta_t\right)^{-(Mt_h+\beta)} = \left(\gamma + \mathrm{tr}\left(\tilde{\mathbf{P}}_{\mathbf{A}}^{\perp}\hat{\mathbf{R}}_{\mathbf{x}}^{(t_h)}\right)\right)^{-(Mt_h+\beta)}, \tag{18}$$

where $\mathrm{tr}(\bullet)$ is the trace operator, $\hat{\mathbf{R}}_{\mathbf{x}}^{(t_h)} = \sum_{t=1}^{t_h} \mathbf{x}_t\mathbf{x}_t^{\mathrm{H}}$, and $\tilde{\mathbf{P}}_{\mathbf{A}}^{\perp} = \mathbf{I}_M - \left(1+\delta^{-2}\right)^{-1}\mathbf{A}\left(\mathbf{A}^{\mathrm{H}}\mathbf{A}\right)^{-1}\mathbf{A}^{\mathrm{H}}$.

Suppose that the state of the Q FDP particles are $\boldsymbol{\Phi} = \left\{\phi_q^{(1)}, \cdots, \phi_q^{(K)}\right\}_{q=1}^{Q}$ at time t_h-1; then, when $\mathbf{x}_{t_h}$ is received, a new group of particles should be generated to fit the new posterior distribution. Since the newly collected snapshot depends on the same FDP as the t_h-1 snapshots, no directional sampling method, such as importance sampling [17], is needed. In our method, we add random perturbations to the old particles to generate a group of new particles for which $\boldsymbol{\Phi}^* = \left\{\phi_q^{(1)*}, \cdots, \phi_q^{(K)*}\right\}_{q=1}^{Q}$, that is,

$$\phi_q^{(k)*} - \phi_q^{(k)} \sim N\left(0, \sigma_\phi^2\right), \qquad k = 1, \cdots, K; q = 1, \cdots, Q, \tag{19}$$

where σ_ϕ^2 is the perturbation variance of the FDP.

The Q candidate particles are then accepted independently with the following probability:

$$\mu = \min\{\xi, 1\}, \tag{20}$$

$$\xi = \left(\frac{\left(\gamma + \mathrm{tr}\left(\tilde{\mathbf{P}}_{\mathbf{A}}^{\perp *}\hat{\mathbf{R}}_{\mathbf{x}}^{(t_h)}\right)\right)}{\left(\gamma + \mathrm{tr}\left(\tilde{\mathbf{P}}_{\mathbf{A}}^{\perp}\hat{\mathbf{R}}_{\mathbf{x}}^{(t_h)}\right)\right)}\right)^{-(Mt_h+\beta)}, \tag{21}$$

where $\tilde{\mathbf{P}}_{\mathbf{A}}^{\perp *} = \mathbf{I}_M - \left(1+\delta^{-2}\right)^{-1}\mathbf{A}^*\left(\mathbf{A}^{*\mathrm{H}}\mathbf{A}^*\right)^{-1}\mathbf{A}^{*\mathrm{H}}$.

We then derive the signal FDPs by averaging the Q accepted particles with weights calculated from (18). As another new snapshot comes in and no frequency hopping is detected, we resample the FDP particles and repeat the procedure described above (as per Algorithm 1, shown below) to update the particles and then obtain a group of new FDPs. As such, we refine the precision of the FDPs as more data is collected during each dwell before another frequency hopping occurs. Otherwise, if frequency hopping is detected, we stop the current refinement procedure, initialize the FDP particles according to Algorithm 2 (shown below), and enter a new FDP update cycle.

2. Frequency Estimation and ARMA Model Establishment

This subsection focuses on obtaining the signal frequency

Algorithm 1. FDP particle update procedure within each dwell.

1. Initialization: Initialize the Q K-dimensional FDP particles according to (8) and set their weights equally.
2. Update: When a new snapshot arrives and no frequency hopping is detected, take the following steps to update the Q particles and their weights.
   - 2.1. Generate particle candidates according to (19).
   - 2.2. Accept candidate particles according to the probability of (20).
   - 2.3. Calculate the normalized particle weights according to the posterior probability shown in (18), that is,

$$w^{(q)}(t_h)=\frac{g\left(\mathbf{\Phi}^{(q)}\middle|\mathbf{x}_{1:t_h}\right)}{\sum_{q=1}^{Q} g\left(\mathbf{\Phi}^{(q)}\middle|\mathbf{x}_{1:t_h}\right)}.$$

   - 2.4. Estimate the signal FDP:

$$\hat{\mathbf{\Phi}}=\sum_{q=1}^{Q} w^{(q)}(t_h)\mathbf{\Phi}^{(q)}.$$

   - 2.5. Resample the Q updated particles to avoid particle degeneracy:

$$\mathbf{\Phi}^{(q)}=\mathbf{\Phi}^{(l(q))},$$

     where $l(q)$ is a selective probability according to the normalized particle weights, that is,

$$p\left(l(q)=i\right)=w^{(i)}(t_h),\quad i=1,\cdots,Q.\pm$$

   - 2.6. Reset the particle weights to $w^{(q)}(t_h)=1/Q$.

Algorithm 2. FDP particle initialization after detection of frequency hopping.

1. For a synchronous network, completely initialize the FDP particles according to (8).
2. For an asynchronous network, initialize only one element in each FDP particle, that is,

$$\mathbf{\Phi}_q^{(k_q)}=\phi,\qquad q=1,\cdots,Q,$$

   where k_q is set randomly from 1 to K and ϕ is generated according to (8).

estimates online and improving their precision when more data is collected so as to establish a more precise ARMA model for frequency hopping detection.

Suppose that the FDP estimates of K signals, denoted by $\hat{\phi}_k$ ($k=1,\ldots,K$), have been obtained from the snapshots $\mathbf{x}_{1:t_h}$, and they form the array responding matrix of $\hat{\mathbf{A}}$. Then, the signal waveforms at times 1 to t_h can be recovered from the maximum posterior perspective according to (16) as

$$\hat{\mathbf{s}}_{1:t_h}=\left(1+\delta^{-2}\right)^{-1}\left(\hat{\mathbf{A}}^{\mathrm{H}}\hat{\mathbf{A}}\right)^{-1}\hat{\mathbf{A}}^{\mathrm{H}}\mathbf{x}_{1:t_h}. \tag{22}$$

As the signal waveforms are pure sinusoids during each dwell, the following equality can be concluded from (1):

$$\mathbf{s}_{2:t_h}=\mathbf{s}_{1:t_h-1}\mathrm{diag}\left\{\left[e^{j\varphi_1},e^{j\varphi_2},\cdots,e^{j\varphi_K}\right]\right\}. \tag{23}$$

Thus, the signal frequencies can be obtained as follows:

$$\begin{aligned}\hat{f}_k^{(t_h)}&=\frac{1}{2\pi T}\mathrm{Ang}\left\{\left[\hat{\mathbf{s}}_{1:t_h-1}^{(k)}\left(\hat{\mathbf{s}}_{1:t_h-1}^{(k)}\right)^{\mathrm{H}}\right]^{-1}\hat{\mathbf{s}}_{1:t_h-1}^{(k)}\left(\hat{\mathbf{s}}_{2:t_h}^{(k)}\right)^{\mathrm{H}}\right\}\\&=\frac{1}{2\pi T}\mathrm{Ang}\left\{\hat{\mathbf{s}}_{1:t_h-1}^{(k)}\left(\hat{\mathbf{s}}_{2:t_h}^{(k)}\right)^{\mathrm{H}}\right\},\end{aligned} \tag{24}$$

where $\hat{\mathbf{s}}_t^{(k)}$ is the k-th element of $\hat{\mathbf{s}}_t$ and $\mathrm{Ang}\{\bullet\}$ stands for the argument of a complex value. The signal frequency estimates derived from (24) do not rely on the unknown signal SNR, and the signal FDP and frequency estimates are paired automatically.

As more snapshots are collected during each dwell, the precision of the FDP estimates improve continuously, and the performance of the signal recovery and frequency estimation derived from (22) and (24) improve accordingly. With the frequency estimates in hand, the ARMA model can be obtained for frequency hopping detection in the next hop instant.

3. Network Sorting

In asynchronous networks, there is only one signal frequency change at a time. Therefore, if signal frequency estimates are obtained before and after each hop, we can associate them according to the frequency continuity of the hop-free signals. However, in synchronous networks, multiple hops can occur simultaneously, so the network sorting can only be realized according to the distinguishable and inactive signal directions, which are estimated according to the FDPs:

$$\hat{\theta}_k=\cos^{-1}\left(C\Big/\left(2\pi\hat{f}_kD\right)\times\hat{\phi}_k\right). \tag{25}$$

During each dwell, after the convergence of the FDPs and frequency estimates, the signal DOA estimates can be calculated according to (25), and they are paired automatically with the frequency estimates. Thus, the DOA estimates in adjacent dwells can be used to associate the frequencies of synchronous networks.

V. Flow of Parameter Estimation and Network Sorting

In this section, we sum up the new method regarding both asynchronous and synchronous networks to provide a more intuitive description.

1. Asynchronous Networks

In Fig. 1, we illustrate the frequency patterns of two asynchronous signals. The lines with different widths in the sketch map are used to represent different signals, and the black

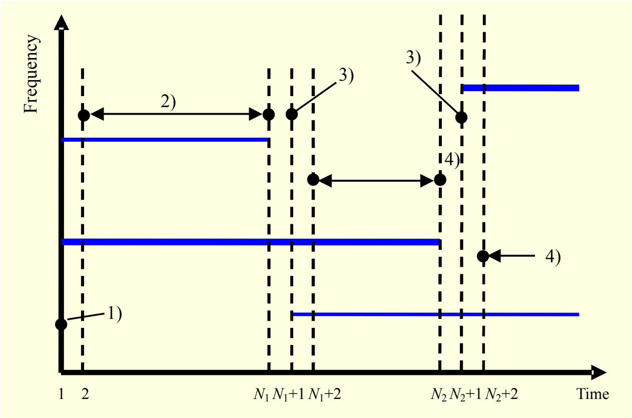

Fig. 1. Flow of parameter estimation and network sorting of asynchronous networks.

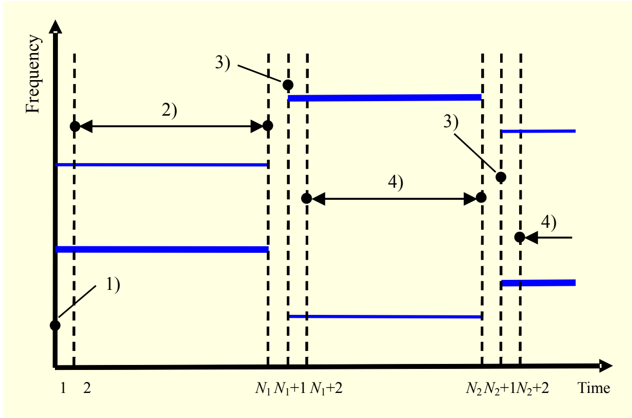

Fig. 2. Flow of parameter estimation and network sorting of synchronous networks.

dots and the arrowheads at the ends of the solid black lines are used to indicate the duration of each process. The bracketed numbers are consistent with the flow of parameter estimation. The actions taken during each process are as follows.

1) Initialize the FDP particles according to (8) after receiving the first array snapshot.

2) Each time a new snapshot arrives, follow Algorithm 1 to update the signal FDP; Recover the signal waveforms according to (22) and (24) to estimate the signal frequencies, then establish the ARMA model with the coefficients calculated according to (3) for hopping detection.

3) When frequency hopping is detected, initialize the FDP particles according to Algorithm 2; If necessary, calculate the signal DOA estimates according to (25) with the frequency and FDP estimates before the predicted hop instant.

4) Apply 2) and compare the frequency estimates before and after the frequency hopping to determine the hopped signal for network sorting or use the DOA estimates to realize it.

2. Parameter Estimation and Network Sorting of Synchronous Networks

In Fig. 2, we illustrate the frequency patterns of two synchronous signals using the same criteria used in Fig. 1. The actions taken during each process are as follows.

1), 2), and 3) are the same as 1), 2), and 3) for asynchronous networks.

4) Apply 2) and calculate the signal directions according to (25) once FDP and frequency estimates converge, then realize network sorting according to the distinguishable DOA of different signals.

VI. Numerical Examples

Suppose that two asynchronous or synchronous FH signals that are simultaneously impinging on a six-element ULA from 70 degrees and 110 degrees depart from the array broadside. The hop bandwidth of each signal is between 50 MHz and 70 MHz, and the frequency bin-width is 2 MHz. The array receiver down-converts the incident signals with a 50-MHz mixer and then samples the result at 70 MHz. The signal frequencies specified below are the down-converted frequencies. The inter-spacing of the ULA equals half the wavelength of the 70-MHz sinusoid. The SNR of each signal is 10 dB, and the adjusting factor of the ARMA-model-based hopping detector is set to 5. For each iteration, 100 particles are used to estimate the signal FDP, and the perturbation variance is set to $\sigma_{\phi}^2 = (0.05\pi)^2$.

1. Case of Asynchronous FH Signals

Suppose that the frequency set of the first signal contains three frequencies; the frequencies are 10 MHz, 14 MHz, and 6 MHz in order, and each frequency holds for a period of 60, 60, and 30 samples, respectively. The frequencies of the second signal are 8 MHz, 16 MHz, and 4 MHz in order, and each holds for a period of 30, 60, and 60 samples, respectively. We then use the proposed method to realize online hop timing and frequency estimation; four hops are detected at the times of the 31st, 61st, 91st, and 121st samples. The real-time frequency estimates and network sorting results are given in Fig. 3, in which "+" and " • " are used to distinguish different signals and the lines stand for the true frequencies. The real-time frequency estimation biases of both signals are shown in Fig. 4, in which the characters are used for signal specification.

It should be noted that the proposed frequency estimator requires at least two snapshots to realize frequency estimation

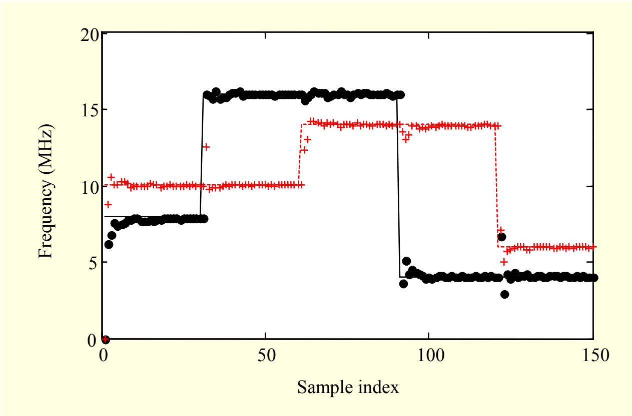

Fig. 3. Result of online frequency estimation and network sorting (asynchronous).

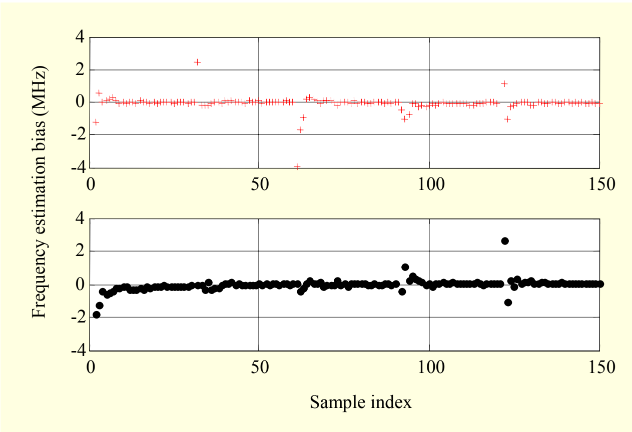

Fig. 4. Bias of frequency estimates (asynchronous).

from recovered waveforms, according to (22) and (24), so no effective frequency estimates are available the moments frequency hopping is detected. To boost visibility, we use the previous frequency estimates at the frequency hopping instants, as shown in Fig. 3, and eliminate the corresponding biases, as shown in Fig. 4.

The simulation results shown in Figs. 3 and 4 imply that the proposed method is able to detect the frequency hops and estimate the frequencies of overlapped asynchronous signals online, and the precision of the frequency estimates increases as more snapshots are collected during each dwell. Moreover, the network sorting can be successfully realized by exploiting the frequency continuity of the hop-free signals. In addition, the signal directions can be calculated from the FDP and frequency estimates, according to (25). We list the DOA estimates at the end of the five dwells in Table 1.

To compare the proposed method with the ARMA model method, we use the probability of detection of the hopping time as a criterion. Suppose that a six-element ULA is used to track the frequencies of two asynchronous FH signals, the signal

Table 1. DOA estimates of asynchronous FH signals.

Sample index		30	60	90	120	150
DOA estimates (°)	Signal 1	70.12	70.29	69.56	70.16	69.97
	Signal 2	109.51	109.94	110.04	109.90	110.16

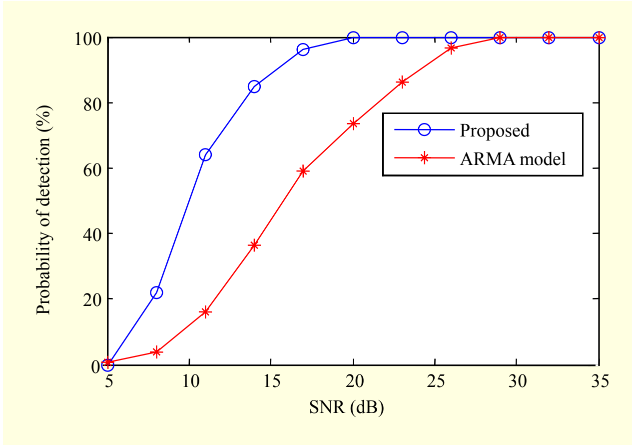

Fig. 5. Probability of correct detection.

frequencies are chosen at random between 2 MHz and 20 MHz with a bin-width of 2 MHz, and one signal hops frequencies at the time of the 17th sample [16]. Detection is deemed correct if the FH is detected at the time of the 17th or 18th sample with the accordant frequencies. In this simulation, we vary the SNR of each signal from 5 dB to 35 dB. The probability curve of correct detection in 200 independent trials is shown in Fig. 5. Observe that the proposed method outperforms the ARMA model method.

2. Case of Synchronous FH Signals

If the two incident FH signals are synchronous, suppose that the frequency sets of the signals are the same as those of the asynchronous signals in the above example, but each frequency dwell of each signal lasts for the duration of 30 samples. Following the proposed method, two frequency hops are detected at the times of the 31st and 61st samples. The online frequency estimates and their biases are shown in Fig. 6 and Fig. 7, in which the different characters are used for signal specification. The simulation results given in Figs. 6 and 7 demonstrate that the proposed method performs well when applied to synchronous FH signals. The corresponding DOA estimates at the end of the three dwells are listed in Table 2.

VII. Conclusion

An online method for hop timing detection and frequency

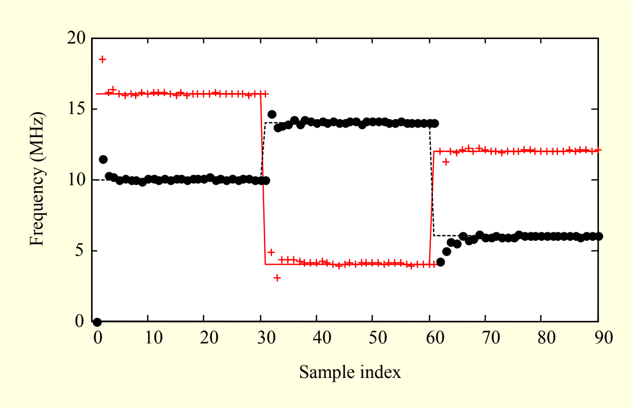

Fig. 6. Result of online frequency estimation and network sorting (synchronous).

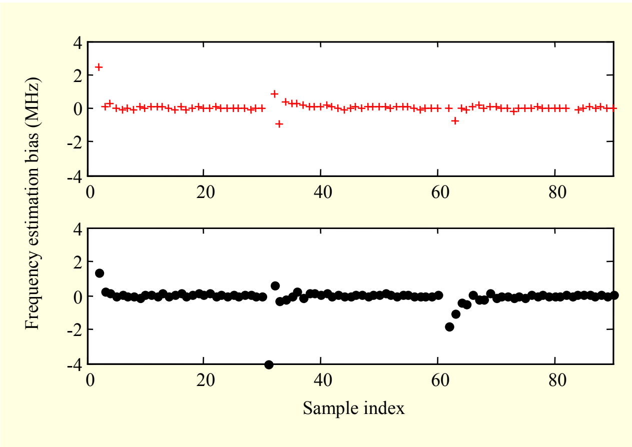

Fig. 7. Bias of frequency estimates (synchronous).

Table 2. DOA estimates of synchronous FH signals.

Sample index		30	60	90
DOA estimates (°)	Signal 1	69.96	69.77	69.75
	Signal 2	110.27	109.83	109.37

estimation, together with network sorting, was proposed in this paper. The method requires no prior knowledge of the frequency set or hop pattern and is applicable to both asynchronous and synchronous FH signals. As the frequency hopping is detected at each instant that a new snapshot arrives, the proposed method adapts to signals with alterable hop rates. If the hop rate is inactive or if such prior information as the frequency set is provided, the proposed method is significantly simplified because only a finite number of hops need to be detected to estimate the signal hop rates or coarse frequency estimates at each dwell need to be obtained to determine which frequencies are selected by the users.

References

[1] C.D. Chung and A. Polydoros, "Detection and Hop-Rate Estimation of Random FH Signals via Autocorrelation Technique," *MILCOM*, 1991, pp. 345-349.

[2] C.D. Chung and A. Polydoros, "Parameter Estimation of Random FH Signals Using Autocorrelation Techniques," *IEEE Trans. Commun.*, vol. 43, no. 2/3/4, Feb./Mar./Apr. 1995, pp. 1097-1106.

[3] M. Janani, V.T. Vakili, and H. Jamali, "The Modified Autocorrelation Technique for Parameter Estimation of Random FH Signals," *Proc. ICSP*, 1998, pp. 188-190.

[4] S. Barbarossa and A. Scaglione, "Parameter Estimation of Spread Spectrum Frequency-Hopping Signals Using Time-Frequency Distributions," *First IEEE Signal Process. Workshop Signal Process. Adv. Wireless Commun.*, 1997, pp. 213-216.

[5] S.G. Mallat and Z. Zhang, "Matching Pursuits with Time-Frequency Dictionaries," *IEEE Trans. Signal Process.*, vol. 41, no. 12, Dec. 1993, pp. 3397-3415.

[6] H. Fan, Y. Guo, and X. Feng, "Blind Parameter Estimation of Frequency Hopping Signals Based on Matching Pursuit," *Wireless Inf. Commun.*, 2008.

[7] C.C. Ko, W. Zhi, and F. Chin, "ML-Based Frequency Estimation and Synchronization of Frequency Hopping Signals," *IEEE Trans. Signal Process.*, vol. 53, no. 2, Feb. 2005, pp. 403-410.

[8] D. Angelosante, G.B. Giannakis, and N.D. Sidiropoulos, "Estimating Multiple Frequency-Hopping Signal Parameters via Sparse Linear Regression," *IEEE Trans. Signal Process.*, vol. 58, no. 10, 2010, pp. 5044-5056.

[9] X. Liu, N.D. Sidiropoulos, and A. Swami, "Blind High-Resolution Localization and Tracking of Multiple Frequency Hopped Signals," *IEEE Trans. Signal Process.*, vol. 50, no. 4, Apr. 2002, pp. 889-901.

[10] X. Liu, N.D. Sidiropoulos, and A. Swami, "Joint Hop Timing and DOA Estimation for Multiple Noncoherent Frequency Hopped Signals," *Sensor Array Multichannel Signal Process. Workshop Proc.*, 2002, pp. 164-168.

[11] X. Liu, N.D. Sidiropoulos, and A. Swami, "Joint Signal Parameter Estimation of Wideband Frequency Hopped Transmissions Using 2-D Antenna Arrays," *4th IEEE Workshop Signal Process. Adv. Wireless Commun.*, 2003, pp. 624-628.

[12] X. Liu, N.D. Sidiropoulos, and A. Swami, "Joint Hop Timing and Frequency Estimation for Collision Resolution in FH Networks," *IEEE Trans. Wireless Commun.*, vol. 4, no. 6, Nov. 2005, pp. 3063-3074.

[13] X. Liu, J. Li, and X. Ma, "An EM Algorithm for Blind Hop Timing Estimation of Multiple FH Signals Using an Array System with Bandwidth Mismatch," *IEEE Trans. Veh. Technol.*, vol. 56, no. 5, Sept. 2007, pp. 2545-2554.

[14] X. Liu, "Signal Detection and Jammer Localization in Multipath Channels for Frequency Hopping Communications," U.S. Army

Research Office project report, DAAD19-03-1-0228, 2005.

[15] L. Acar and R.T. Compton, "The Performance of an LMS Adaptive Array with Frequency Hopped Signals," *IEEE Trans. Aerospace Electron. Syst.*, vol. AES-21, no. 3, May 1985, pp. 360-371.

[16] Z.M. Liu, Z.T. Huang, and Y.Y. Zhou. "Hopping Instants Detection and Frequency Tracking of Frequency Hopping Signals with Single or Multiple Channels," *IET Commun.*, vol. 6, no. 1, 2012, pp. 84-89.

[17] J.R. Larocque, J.P. Reilly, and W. Ng, "Particle Filters for Tracking an Unknown Number of Sources," *IEEE Trans. Signal Process.*, vol. 50, no. 12, Dec. 2002, pp. 2926-2937.

[18] Z.M. Liu et al., "Improved Gerschgorin Disk Estimator for Source Enumeration with Robustness against Spatially Non-uniform Noise," *IET Radar*, *Sonar*, *Nav.*, vol. 5, no. 9, 2011, pp. 952-957.

[19] Z.M. Liu, Z.T. Huang, and Y.Y. Zhou, "Computationally Efficient Direction Finding Using Uniform Linear Arrays," *IET Radar*, *Sonar*, *Nav.*, vol. 6, no. 1, 2012, pp. 39-48.

[20] C. Andrieu and A. Doucet, "Joint Bayesian Model Selection and Estimation of Noisy Sinusoids via Reversible Jump MCMC," *IEEE Trans. Signal Process.*, vol. 47, no. 10, Oct. 1999, pp. 2667-2676.

Zhi-Chao Sha received his BS and MS in information and communication engineering in 2007 and 2010, respectively, from the School of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China. He is currently working toward his PhD at the School of Electronic Science and Engineering, National University of Defence Technology. His research interests include communication signal processing and array signal processing.

Zhang-Meng Liu received his BS and PhD in information and communication engineering in 2006 and 2012, respectively, from the School of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China. Currently, he is a lecturer in the School of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China. His research interests include array signal processing and compressive sensing.

Zhi-Tao Huang received his BS and PhD in information and communication engineering in 1998 and 2003, respectively, from the School of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China. He is now a professor with the College of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China. His research interests include radar and communication signal processing and array signal processing.

Yi-Yu Zhou received his BS, MS, and PhD in information and communication engineering from the School of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China, in 1982, 1985, and 1992, respectively. He is currently a professor with the College of Electronic Science and Engineering, National University of Defense Technology, Changsha, Hunan, P.R. China. His research interests include radar signal processing and passive location.