WSN Signal Online Blind Extracting Algorithm Based on UKF

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***Abstract* — In order to solve the problem that the online blind extracting algorithm used for wireless sensor network has relatively large extracting error in noisy environment, the article proposes a new blind extracting algorithm based on unscented Kalman filter (UKF). This algorithm is realized through recursion, and two UKFs alternatively work during each recursion to respectively estimate the extracted vector and the source signal. The simulation result shows that the algorithm can effectively extract the interested source signal; and compared with the existing blind extracting algorithm based on UKF, the extracting performance of this algorithm in noisy environment is obviously improved.**

Keywords - wireless sensor network; blind extracting; unscented kalman filter (UKF)

I. INTRODUCTION

Due to the unique advantages of low cost, small power consumption, easy network arrangement, etc., wireless sensor network has been widely applied in such fields as industry, livelihood, environmental protection and medical treatment [1-2]. However, due to the dispersibility of the sensor nodes and the complexity of the operating environment as well as the unpredictability of the interference signal, new challenges are proposed to the signal processing technology of the wireless sensor network: if both the interested signal source and the interference source are not narrow-band signals, the integration of the signals collected from various sensor nodes cannot be modeled as the simple superposition of source signal, narrow-band signal and Gaussian signal [3], so the signals cannot be extracted through traditional frequency domain filtering mode. If the signal channel parameters are unknown and the most statistical properties of the interference signal and the source signal to be extracted are also unknown, the traditional filtering algorithm is no longer effective and the blind extracting technology shall be used to reestablish source signal [4-6].

Literatures adopt second-order statistics to extract the signals acquired by wireless sensor network, and this method requires the source signals have different time structures and the extracted signals have amplitude and sequence uncertainty. Also, some scholars pre-code the source signal and extract specific source signal in sensor network by virtue of the coded message, and it is difficult to realize this method in most applications. Literatures adopt nonlinear Kalman filter to extract the linear mixed signals acquired by wireless sensor network [7].

The dynamic characteristics of the source signal to be extracted are assumed to be known in this type of algorithms and such assumption is usually reasonable for actual application [8-10]. For example, in the wireless sensor network used for environment monitoring, the integration center has known the dynamic characteristics of temperature, humidity, etc. along with the alternate change of day and night or seasons; in passive radar system, the receiver has known the dynamic structure of the transmitted signal when estimating the target parameter. These algorithms convert the blind extracting issue into a nonlinear state estimation issue and meanwhile adopt Kalman filter for solution. However, these algorithms are very sensitive to noise and are not suitable for the application under low SNR (signal to noise ratio) condition. In order to solve such problem, the article proposes a new online blinding extracting algorithm based on existing UKF algorithm, and this algorithm can make full use of the useful information of the node observation signal to have better performance in noisy environment.

II. MATERIAL AND METHODS

The wireless sensor network system with m observation nodes is considered in the article to observe the independent source signal mixed by n unknown signal channels. n -dimension source signal vector is mixed through unknown hybrid matrix $\boldsymbol{A} \in R^{m\times n}$ and m -dimension observation vector $\boldsymbol{x}_k = [x_{1,k},...,x_{m,k}]^T$ is obtained from observing m sensor nodes, and $\{\hat{s}_{1,k}, \hat{s}_{2,k}, \ldots\}$ is the source signal recovered from the node observation data through the blind extracting algorithm, as shown in Fig. 1.

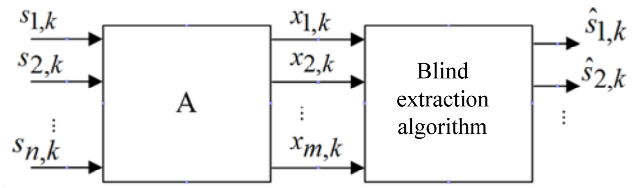

Figure 1. Blind extracting problem model

The transmission relation between source signal vector and node observation vector is:

$$\boldsymbol{x}_k = \boldsymbol{A}\boldsymbol{s}_k + \boldsymbol{n}_k \tag{1}$$

Therein, the observation noise $\boldsymbol{n}_k = [n_{1,k},...,n_{m,k}]^T$ is mutually unrelated Gaussian white noise and $\boldsymbol{R}$ is covariance matrix. The online blind extracting algorithm aims at recovering one or more needed source signals $s_{j,k}$ ($j = 1,2,...n$) from the mixed signal $\boldsymbol{x}_k$ superposed with observation noise. Specifically, the integration center orderly receives the sampling value $\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2,...]$ of the observation vector sensed by various nodes and then estimates the value of the source signal at time k according to existing and previous data after a certain sampling value $\boldsymbol{x}_k$ arrives, wherein the mean square error $\| \hat{s}_k - s_{j,k} \|^2$ of the estimated value $\hat{s}_k$ thereof and the true value $s_{j,k}$ of the source signal shall be minimized. The above problem can be converted into the problem of solving an optimal extracted vector $\boldsymbol{w}_k = [w_{1,k},..., w_{m,k}]$: use KUF to find the estimated value $\hat{\boldsymbol{w}}_k$ of $\boldsymbol{w}_k$ and make the extracted signal.

$$\hat{s}_k = \hat{\boldsymbol{w}}_k^T \cdot \boldsymbol{x}_k \tag{2}$$

maximally approach to the source signal $s_{j,k}$.

For the rest parts of the article, the blind source extracting model (1) is assumed as follows:

1) The number of source signals can be unknown but shall not be more than the number of the observation nodes, namely $n \le m$;

2) The source signals are statistically independent of each other;

3) The source signals to be extracted are generated by known dynamic system, namely:

$$s_{j,k} = f\left(s_{j,k-1}\right) \tag{3}$$

Therein $f(\cdot)$ refers to the known nonlinear function.

4) Hybrid matrix $\boldsymbol{A}$ has full column rank.

III. UKF ALGORITHM

The state transition equation of the nonlinear system to be estimated is assumed as:

$$\boldsymbol{z}_k = F\left(\boldsymbol{z}_{k-1}\right) + \boldsymbol{e}_{k-1} \tag{4}$$

The observation equation is:

$$\boldsymbol{y}_k = H\left(\boldsymbol{z}_k\right) + \boldsymbol{n}_k \tag{5}$$

Therein, $\boldsymbol{z}_k$ is state vector, $\boldsymbol{y}_k$ is observation vector, $\boldsymbol{e}_k$ is system noise and $\boldsymbol{n}_k$ is observation noise; $\boldsymbol{e}_k$ and $\boldsymbol{n}_k$ are mutually unrelated zero-mean Gaussian white noise, and the covariance matrixes thereof are respectively $\boldsymbol{Q}$ and $\boldsymbol{R}$; $F(\cdot)$ and $H(\cdot)$ are respectively nonlinear state transition function and observation function.

UKF algorithm adopts prior covariance matrix of the state variable to generate a series of sigma points through unscented conversion; then, the mean value and the predicted value of the covariance of these sigma points are calculated by weight after nonlinear function propagation. There is no linear approximation for nonlinear state transition function in UKF algorithm as that in EKF algorithm or Jacobian matrix calculation, so both the performance and the execution efficiency of UKF algorithm are superior to EKF algorithm under most circumstances. UKF unscented conversion coefficient is determined by following formulae:

$$\begin{cases} \mu_0^{(m)} = \dfrac{\lambda}{m+\lambda}, \mu_0^{(c)} = \dfrac{\lambda}{m+\lambda} + \left(1-\alpha^2+\beta\right) \\ \mu_i^{(m)} = \mu_i^{(c)} = \dfrac{1}{2\left(m+\lambda\right)} \qquad i = 1,...2m \\ \lambda = \alpha^2\left(m+\kappa\right) - m \\ \gamma = \sqrt{m+\lambda} \end{cases} \tag{6}$$

Therein, parameter α determines the dispersity of sigma points around the mean value and is usually set as $1e-4 \le \alpha \le 1$; parameter β is used to implant the prior knowledge regarding state variable distribution, and is hereby assumed as Gaussian distribution and set as $\beta = 2$; κ is a scale parameter and here set as $\kappa = 0$.

UKF algorithm adopts recursion form and each recursion after initialization includes two steps, namely prediction and observation updating.

① Initialization:

$$\hat{\boldsymbol{z}}_0 = E[\boldsymbol{z}_0] \quad \boldsymbol{P}_0 = E[\left(\boldsymbol{z}_0 - \hat{\boldsymbol{z}}_0\right)\left(\boldsymbol{z}_0 - \hat{\boldsymbol{z}}_0\right)^T] \tag{7}$$

② Prediction:

$$\boldsymbol{Z}_{k-1} = [\hat{\boldsymbol{z}}_{k-1} \ \hat{\boldsymbol{z}}_{k-1} + \gamma\sqrt{\boldsymbol{P}_{k-1}} \ \ \hat{\boldsymbol{z}}_{k-1} - \gamma\sqrt{\boldsymbol{P}_{k-1}}\,] \tag{8}$$

$$\boldsymbol{Z}_{k|k-1}^* = F\left(\boldsymbol{Z}_{k-1}\right) \tag{9}$$

$$\hat{\boldsymbol{z}}_k^- = \sum_{i=0}^{2m} \mu_i^{(m)} \boldsymbol{Z}_{i,k|k-1}^* \tag{10}$$

$$\boldsymbol{P}_k^- = \sum_{i=0}^{2m} \mu_i^{(c)} \left(\boldsymbol{Z}_{i,k|k-1}^* - \hat{\boldsymbol{z}}_k^-\right)\left(\boldsymbol{Z}_{i,k|k-1}^* - \hat{\boldsymbol{z}}_k^-\right)^T + \boldsymbol{Q} \tag{11}$$

The prediction process expressed by formulae (8) ~ (11) is simply recorded as $[\hat{\boldsymbol{z}}_k^-, \boldsymbol{P}_k^-] = ukfpredict(\hat{\boldsymbol{z}}_{k-1}, \boldsymbol{P}_{k-1})$,

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therein, $\hat{\boldsymbol{z}}_{k-1}$ and $\boldsymbol{P}_{k-1}$ respectively stand for the state variable mean value and the covariance posteriori estimation obtained in previous recursion, $\hat{\boldsymbol{z}}_k^-$ and $\boldsymbol{P}_k^-$ respectively stands for present state variable mean value and covariance posteriori estimation.

③Observation updating:

$$\boldsymbol{Z}_{k|k-1} = [\hat{\boldsymbol{z}}_k^- \;\; \hat{\boldsymbol{z}}_k^- + \gamma\sqrt{\boldsymbol{P}_k^-} \;\; \hat{\boldsymbol{z}}_k^- - \gamma\sqrt{\boldsymbol{P}_k^-}] \tag{12}$$

$$\boldsymbol{Y}_{k|k-1} = H\left(\boldsymbol{Z}_{k|k-1}\right) \tag{13}$$

$$\hat{\boldsymbol{y}}_k^- = \sum_{i=0}^{2m} \mu_i^{(m)} \boldsymbol{Y}_{i,k|k-1} \tag{14}$$

$$\boldsymbol{P}_{yy} = \sum_{i=0}^{2m} \mu_i^{(c)} \left(\boldsymbol{Y}_{i,k|k-1}^* - \hat{\boldsymbol{y}}_k^-\right)\left(\boldsymbol{Y}_{i,k|k-1}^* - \hat{\boldsymbol{y}}_k^-\right)^T + \boldsymbol{R} \tag{15}$$

$$\boldsymbol{P}_{zy} = \sum_{i=0}^{2m} \mu_i^{(c)} \left(\boldsymbol{Z}_{i,k|k-1} - \hat{\boldsymbol{z}}_k^-\right)\left(\boldsymbol{Y}_{i,k|k-1} - \hat{\boldsymbol{y}}_k^-\right)^T \quad 16)$$

$$\boldsymbol{K}_k = \boldsymbol{P}_{zy} \boldsymbol{P}_{yy}^{-1} \tag{17}$$

$$\hat{\boldsymbol{z}}_k = \hat{\boldsymbol{z}}_k^- - \boldsymbol{K}_k\left(\boldsymbol{y}_k - \hat{\boldsymbol{y}}_k^-\right) \tag{18}$$

$$\boldsymbol{P}_k = \boldsymbol{P}_k^- - \boldsymbol{K}_k \boldsymbol{P}_{yy} \boldsymbol{K}_k^T \tag{19}$$

The observation updating process expressed by formulae (12) ~ (19) is simply recorded as follows:

$$[\hat{\boldsymbol{z}}_k, \boldsymbol{P}_k] = ukfupdate(\hat{\boldsymbol{z}}_k^-, \boldsymbol{P}_k^-)$$

wherein $\hat{\boldsymbol{z}}_k$ and $\boldsymbol{P}_k$ respectively stand for the state variable mean value and the covariance posteriori estimation at present recursion.

IV. ONLINE BLIND EXTRACTING ALGORITHM

The blind extracting algorithms mentioned in literatures both adopt a nonlinear Kalman filter for the recursion and estimation of the extracted vector $\hat{\boldsymbol{w}}_k$, and then the observation signal and $\hat{\boldsymbol{w}}_k$ are directly multiplied to extract source signal. On the basis of following the extracted vector solving method mentioned in literatures, the article introduces another (the second) UKF to extract source signal, and the two UKFs alternately work to respectively estimate the extracted vector and the source signal. [23]

A. *Solving of Extracted Vector*

Hybrid matrix $\boldsymbol{A}$ is not changed along with time, so the optimal value of the extracted vector $\boldsymbol{w}_k$ is also time-invariant. On this basis, the state transition equation of estimation $\hat{\boldsymbol{w}}_k$ of the extracted vector is as:

$$\hat{\boldsymbol{w}}_k = \hat{\boldsymbol{w}}_{k\text{-}1} + \boldsymbol{e}_{k\text{-}1} \tag{20}$$

In the formula, $\boldsymbol{e}_k$ is process noise and the covariance matrix thereof is $\boldsymbol{Q}$. Theoretically, the process noise of the time-invariant extracted vector is 0, but in order to prevent the state variable covariance matrix from being not positive definite or singular during the recursion process, $\boldsymbol{Q}$ is hereby set as $\boldsymbol{Q} = diag[10^{-8}]$. Additionally, the estimation $\hat{s}_k$ of the source signal $s_{1,k}$ to be extracted shall meet the nonlinear equation (3) corresponding to the source signal $s_{1,k}$. Integrate formulae (2), (3) and (20) to obtain the observation equation of the extracted vector $\hat{\boldsymbol{w}}_k$:

$$\hat{\boldsymbol{w}}_k^T \cdot \boldsymbol{x}_k = f\left(\hat{\boldsymbol{w}}_k^T \cdot \boldsymbol{x}_{k\text{-}1}\right) + n_k \tag{21}$$

In the formula, n_k is one-dimension noise vector. According to formulae (20) and (21), adopt the observation data $\boldsymbol{x}_k$ to solve the extracted vector $\hat{\boldsymbol{w}}_k$ in each recursion through UKF method mentioned in previous section.

B. *Estimation of Source Signal*

In literatures, formula (2) is directly used to solve source signal $\hat{s}_k$ after the extracted vector $\hat{\boldsymbol{w}}_k$ is obtained. Due to the negligence of the influence of the additive observation noise in formula (1), the performance is significantly reduced under the existence of noise. Therefore, the second UKF can be introduced therein to take the source signal $\hat{s}_k$ as state variable for estimation. $\hat{s}_k$ state equation can be obtained through formula (3):

$$\hat{s}_k = f\left(\hat{s}_{k-1}\right) + u_{k-1} \tag{22}$$

Therein, u_k is one-dimension process noise and the processing method can be the same as that of e_k in formula (20). Since the extracted vector at time k is obtained in previous section, thus the extracted vector $\bar{\boldsymbol{w}}_k$ at this moment is hereby assumed to be known. $\bar{\boldsymbol{w}}_k^T \cdot \boldsymbol{x}_k$ is regarded as the observation value in order to obtain the observation equation through formula (2):

$$\bar{\boldsymbol{w}}_k^T \cdot \boldsymbol{x}_k = \hat{s}_k + n_k \tag{23}$$

Through UKF, the source signal can be estimated in each recursion according to formulae (22) and (23). The whole online blind extracting algorithm can be described by following pseudo-codes:

$$\hat{\boldsymbol{w}}_0 = E\left(\boldsymbol{w}_0\right) \quad \boldsymbol{P}_{w_0} = E[\left(\boldsymbol{w}_0 - \hat{\boldsymbol{w}}_0\right)\left(\boldsymbol{w}_0 - \hat{\boldsymbol{w}}_0\right)^T]$$

$$\hat{s}_0 = E\left(s_0\right) \quad \boldsymbol{P}_{s_0} = E[\left(s_0 - \hat{s}_0\right)\left(s_0 - \hat{s}_0\right)^T]$$

$$For\ k \in \{1, 2, \ldots, \infty\}$$

UKF Process I: solve the extracted vector:

$$\begin{cases} [\hat{\boldsymbol{w}}_k^-, \boldsymbol{P}_{w_k}^-] = ukfpredict(\hat{\boldsymbol{w}}_{k\text{-}1}, \boldsymbol{P}_{w_{k-1}}) \\ [\hat{\boldsymbol{w}}_k, \boldsymbol{P}_{w_k}] = ukfupdate(\hat{\boldsymbol{w}}_k^-, \boldsymbol{P}_{w_k}^-) \end{cases}$$

UKF Process II: estimate source signal:

$$\begin{cases}[\hat{s}_k^-, \boldsymbol{P}_{s_k}^-] = ukfpredt(\hat{s}_{k-1}, \boldsymbol{P}_{s_{k-1}}) \\ [\hat{s}_k, \boldsymbol{P}_{s_k}] = ukfupdate(\hat{s}_k^-, \boldsymbol{P}_{s_k}^-)\end{cases}$$

End For

According to the definition of Kalman filter, the extracted vector $\hat{\boldsymbol{w}}_k$ and the extracted signal $\hat{s}_k$ obtained from online algorithms are both the optimal estimation under minimum mean square error.

V. SIMULATION EXPERIMENT

The section will evaluate the algorithm performance through two simulation experiments which are carried out in Matlab software. On the one hand, the blind extracting effect is visually compared through the waveforms of the source signal and the extracted signal; on the other hand, the blind extracting effect is quantitatively analyzed through calculating the mean square error of the extracted signal under different input SNRs. Additionally, the mean square error of the extracted signal is defined as:

$$MSE(dB) = 10\lg\left[N^{-1} \cdot \sum_{i=1}^{N} \left|\hat{s}(i) - s(i)\right|^2\right] \quad (24)$$

The experimental result of the quantitative analysis is obtained from Monte-Carlo simulations.

A. *Simulation Experiment 1*

Two chaotic sequences are taken as source signal:

$$s_1(k) = s_1^2(k-1) - 2,$$

$$s_2(k) = 1 + \sin(\pi\, s_2(k-1))$$

$$A = \begin{bmatrix} 0.3587 & -0.4145 \\ 0.1021 & 0.2312 \end{bmatrix}$$

Mix the source signals according to formula (1) through the hybrid matrix $A = \begin{bmatrix} 0.3587 & -0.4145 \\ 0.1021 & 0.2312 \end{bmatrix}$ randomly generated in the interval of $[-1,1]$, wherein the source signal to be extracted is s_1.

Fig. 2 shows one segment of the oscillograms of the source signal and the extracted signal after the algorithm convergence at SNR of 24dB. According to the figure, the existing UKF extracting algorithm and the algorithm proposed in the article both can finish the extracting task for the source signal, but after careful comparison of each sample point of the extracted signal and the source signal, we can know that the signal extracted by the algorithm proposed in the article is more approximate to the source signal.

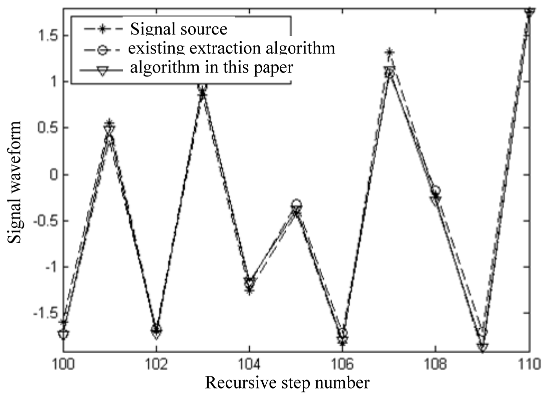

Figure 2. Waveform comparison of source signal and extracted signal

Fig. 3 shows the mean square errors of the source signals and the extracted signals under different input SNRs. Obviously, when the input SNR is lower than 55dB, the error of the signal extracted by the algorithm proposed in the article is lower than that extracted by existing UKF blind extracting algorithm; but when the input SNR is very high, the algorithm performance will be reduced more or less, indicating that compared with the blind extracting algorithm based on Kalman filter framework, the algorithm proposed in the article has obviously improved performance in noisy environment.

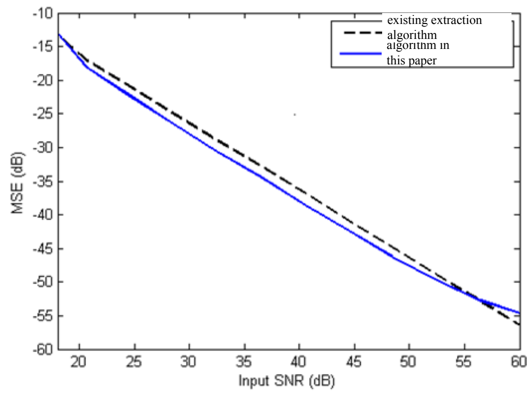

Figure 3. MSE/SNR performance of blind extracting algorithm

B. *Simulation Experiment 2*

Simulation experiment 2: two chaotic sequences and one sinusoidal signal

$$s_1(k) = 1 - 2s_1^2(k-1)$$

$$s_2(k) = \cos(4\arccos s_2(k-1))$$

$$s_3(k) = \sin(0.02\pi k)$$

$$A = \begin{bmatrix} 0.2939 & 0.2169 & -0.8132 \\ 0.7621 & -0.5995 & 0.3523 \\ 0.1062 & -0.4315 & 0.3789 \end{bmatrix}$$

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Mix the source signals according to formula (1) through the hybrid matrix $A = \begin{bmatrix} 0.2939 & 0.2169 & -0.8132 \\ 0.7621 & -0.5995 & 0.3523 \\ 0.1062 & -0.4315 & 0.3789 \end{bmatrix}$ randomly generated in the interval of $[-1,1]$, wherein the source signal to be extracted is s_1.

Fig. 4 shows one segment of the oscillograms of the source signal and the extracted signal after the algorithm convergence at SNR of 24dB. According to the figure, the algorithm proposed in the article has higher precision.

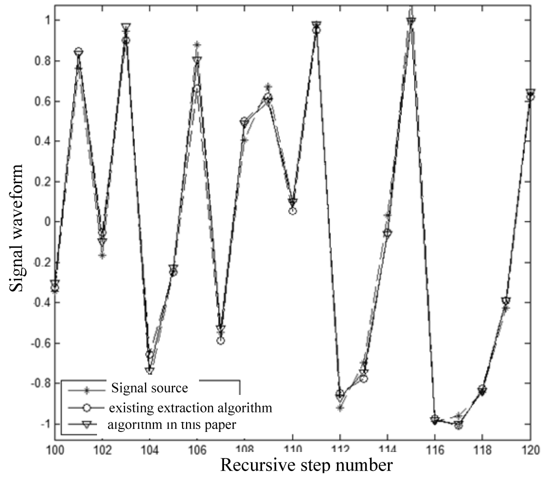

Figure 4. Waveform comparison of source signal and extracted signal

Fig. 5 shows the quantitative comparison of the errors of the two algorithms. When the input mixed signal is superposed with certain additive noise, the algorithm mentioned in the article has smaller extracting error.

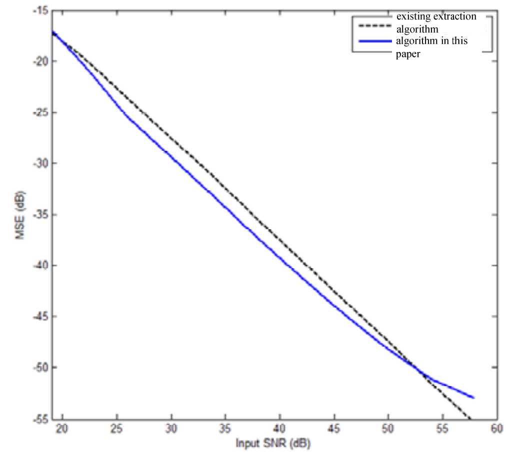

Figure 5. MSE/SNR performance of blind extracting algorithm

VI. CONCLUSION

The article has proposed an online blind extracting algorithm used for wireless sensor network. In allusion to the problem of the performance reduction of the existing Kalman blind extracting algorithms in additive noisy environment, this algorithm introduces the second Kalman filter to reconstruct the source signal on the basis of existing blind extracting algorithm in order to effectively reduce extracting error and improve extracting performance. Meanwhile, the whole algorithm is realized in UKF framework and there is no need to calculate the higher-order statistics of the observation signal and the gradient of the cost function, so the algorithm has small computation burden and is especially suitable for the wireless sensor networks sensitive to computation load.

VII. CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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