Research on Single Antenna Co-frequency Mixed Signal Separation Based on Improved EFICA Algorithm

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Abstract: Signal separation under the condition of single antenna reception is a process of estimating the source signal component by using one-dimensional observation signal vector. Under the condition of single antenna receiving the same-frequency mixed signal, in view of the problem that the stability of the EFICA algorithm will be affected by the selection of a random initial iterative matrix, it is proposed to use the steepest descent method to select a suitable iterative initial matrix to improve the EFICA algorithm. An experimental comparison between the EFICA algorithm and the EFICA improved algorithm is presented. The simulation results show that the improved EFICA algorithm can achieve a better separation effect for the separation of mixed signals at the same frequency.

1. Introduction

With the rapid development and wide application of wireless communication technology, the sky is full of various communication signals, so there is a lot of mixed signals. The mixed signals here are aliased in the time domain and frequency domain [1], resulting in frequency spectrum as resources are becoming increasingly scarce, the processing of mixed signals becomes particularly important. More and more communication or radar signals occupy the same frequency band. For example, in the 2.4GHz frequency band, there are wireless LAN signals and wireless personal area network signals that follow the IEEE 802.11 protocol at the same time. At 1176MHz and 1575MHz frequency points, there are American GPS systems. The signal of the European Galileo system also exists [2]. In daily radio monitoring, it is often encountered that two signals with the same carrier frequency but different strengths are mixed together for transmission. This interference seriously affects normal wireless communication services, and radio monitoring needs to focus on one of the problems solved [3]. In the environment of satellite channels, there are also a large number of mixed signals with the same frequency, and the causes are mainly divided into the following situations. One is the interference from the ground, which mainly includes the interference caused by the communication system of the same frequency band on the ground and the echo interference between the satellite receiving terminal and the gateway. The second is interference...
from space, which is mainly interference from neighboring stars. The third is the adoption of new satellite communication systems, such as satellite paired carrier multiple access (Paired Carrier Multiple Access) technology [4].

At present, domestic research in this field, the existing separation algorithms are mainly focused on separation methods based on particle filtering and one-by-one surviving path processing. The latter is used in the single-antenna automatic identification system (AIS), which makes the number of observable ships large. Improve [5]. Foreign research on this issue is earlier, the ALQ-218V(2) tactical receiver equipped with the ICAP-3 special electronic warfare aircraft of the United States can achieve electronic monitoring while completing full-frequency interference to the enemy. Efficacy [6]. There are four main co-frequency signal separation techniques, namely, strong signal recovery method, ICA algorithm, FastICA algorithm and particle filter algorithm [7]. The ICA algorithm is an extension of the PCA algorithm. It finds one A linear transformation to minimize the statistical dependence between the components, has the potential to be applied in blind recognition, source location, data analysis and compression [8]. FastICA algorithm is a fast independent component analysis (Independent Component Analysis) algorithm it is an algorithm based on Newton’s iterative method and reasonable approximation [9], so it has room for improvement. In recent years, many improved Newton’s iterative methods with higher-order convergence properties have been proposed. The particle filter algorithm is based on Monte Carlo the approximate Bayesian filtering algorithm of Luo simulation is widely used in nonlinear and non-Gaussian state estimation problems [10].

The EFICA algorithm cannot eliminate the influence of the selected random initial matrix on the convergence stability of the Newton iteration method. This article proposes an improvement to the EFICA algorithm, choose a suitable initial iteration matrix, research on the separation of single antenna co-frequency mixed signal. Then a simulation platform was built in the Matlab software environment to model the source signal and the mixed signal. The mixed signal was separated using the EFICA algorithm and the improved EFICA algorithm, and the average correlation coefficient was used to compare the separation performance of each algorithm. The simulation experiment results show that for the separation of the same-frequency mixed signal, the improved EFICA algorithm effectively improves the algorithm stability, and the separated signal is closer to the source signal.

2. Mixed signal model
Consider a single antenna receiving two mixed signals of the same frequency. The general form of signal reception is:

\[ y(t) = x_1(t) + x_2(t) + v(t) \]  

(1)

In the above formula, \( v(t) \) is zero-mean additive white Gaussian noise with a power spectral density of \( N_0 / 2 \). \( x_1(t) \) and \( x_2(t) \) are the two received signals with the same frequency, which can be further expressed as:

\[ x_1(t) = A_1 \sin(\omega t + \varphi_1) \]

(2)

\[ x_2(t) = A_2 \cos(\omega t + \varphi_2) \]

(3)

In the above equations 2 and 3: is the local carrier frequency; A1 and A2 are the amplitudes of the two signals at the same frequency; 1, 2 are the initial phases; \( g_1(t) \) and \( g_2(t) \) are equivalent channel filters. The impulse response (including the transmitting filter, the channel filter and the receiving filter). If the transmitting filter matches the receiving filter, the equivalent filter will have a raised cosine impulse response, which will be a response with a completely determined rolling coefficient. Next, we assume that the rolling coefficient is known; the two signals have the same symbol period, T is the symbol period; \( 0 \leq \tau_1(t) < T \) is the time delay between the local reference clock and the received signal.

Assuming that the duration of the raised cosine waveform is \([1-L,LT] \), the (1) signal is down-converted and sampled at a rate of 1/T to obtain
3. Improved EFICA algorithm to separate the same frequency mixed signal

3.1. Improved EFICA algorithm

The EFICA algorithm cannot eliminate the new influence of the selected random initial matrix on the convergence and stability of Newton's method. In this paper, the improved EFICA algorithm can select a suitable initial matrix for iteration, is insensitive to the initial value and the iteration speed is faster.

There are six steps to improve the EFICA algorithm:

Step 1: to average and whiten the mixed signal of the same frequency. It is to avoid the influence of signal strength, amplitude and other factors during the separation process. This treatment will not affect the separation effect, which is:

\[
\hat{\mathbf{C}} = (\mathbf{X} - \hat{\mathbf{X}})(\mathbf{X} - \hat{\mathbf{X}})^T / N \tag{5}
\]

\[
\mathbf{Z} = \hat{\mathbf{C}}^{-1/2} (\mathbf{X} - \hat{\mathbf{X}}) \tag{6}
\]

In the above formula, is the sample covariance matrix, is the average value of the mixing matrix, and is the observation signal including the preprocessing.

Step 2: Use the steepest descent method to select the appropriate initial iteration matrix. Randomly generate an initial iterative matrix, and orthogonalize it to get. Calculate the negative gradient value at W. If, is a very small positive number, it is used as the convergence threshold. If it converges, then W at this time is the appropriate initial iterative matrix. If it does not converge, then return to the step to calculate the negative gradient of W until convergence.

Step 3: Use the initial iterative matrix selected above to process the observation signal based on the maximum judgment criterion until it converges. The initial iterative matrix is obtained in the second step, and the iteration process is as follows:

\[
W^{+}(K + 1) = g[W(k)Z][Z^T - \text{diag} \{g'(W(k)Z)\}W(k)]W(k) \tag{7}
\]

In the above formula, g and g' represent the first and second derivatives of G, 1N represents a column of vectors, and k is the number of iterations. And is a non-linear function often used.

Step 4: select an adaptive nonlinear function, first estimate the fourth moment of the signal sample, and determine whether the selected nonlinear function is close enough to the evaluation function. If it is not close to the evaluation function, a more suitable adaptive nonlinear function should be selected. If the signal distribution is a generalized Gaussian distribution, the evaluation function of the EFICA algorithm is:

\[
g_k(x) = \begin{cases} 
    x \exp(-\eta k |x|) & \hat{m}_{4k} > 3 \\
    |x|^{\min[\eta k, -1.14]} \text{sign}(x) & 1.8 < \hat{m}_{4k} \leq 3 \\
    |x|^{1.4} \text{sign}(x) & \hat{m}_{4k} \leq 1.8 
\end{cases} \tag{8}
\]

In the above formula, \( \hat{m}_{4k} = \frac{1}{N} \hat{C}^4_k / N \) is the estimated value of the fourth-order matrix of the estimated source signal, (where \( \hat{m}_{4k} \) is the fourth-order moment of a single source signal) \( \hat{\alpha}_k = [v_1(\hat{m}_{4k} - 1.8)^{1/2} - v_2(\hat{m}_{4k} - 1.8)]^{-1} \), \( v_1 = 0.2096 \), \( v_2 = 0.1851 \), \( \phi_1 = 3.348 \).

Step 5: Use to iterate, the iteration process is:
\[
W^+(K + 1) = g[W(k)Z]Z^T - \text{diag}[g[W(k)Z]W(k)] \\
W^+(K + 1) = \text{diag}[c_1 \ldots c_d]W^+(k) \\
W(K + 1) = [W^+(k)W^+(k)^T]^{-1/2}W^+(k)
\] (9)

Step 6: Carry out signal separation, the separated signal is \(y = WZ\).

The improved EFICA algorithm is compared with the EFICA algorithm. The steps of the improved algorithm after selecting the initial iterative matrix remain unchanged from the original algorithm. Although using the steepest descent method is equivalent to adding one more step to the original algorithm, it does not waste much time due to its fast initial iteration speed. And due to the suitability of the initial iterative matrix, the subsequent algorithm will proceed smoothly, and there will not be too many convergence times or even failure to converge. From the overall point of view of the improved algorithm, the speed will not necessarily be reduced, or even faster, but the stability will be improved.

3.2. Improved EFICA algorithm separation process

The first step uses the FastICA algorithm based on the largest negative entropy. This paper takes the largest negative entropy as the search direction, extracts the independent sources in order, and uses a fixed-point iterative optimization algorithm to make the convergence faster and more stable. The expression of the differential entropy of the random variable \(Y\) is:

\[
H(Y) = -\int p_Y(\xi) \log p_Y(\xi) d\xi
\] (10)

\(Y_{Gauss}\) Is a Gaussian random variable with the same variance as the random variable, the negative entropy of the random variable \(Y\) is:

\[
N_y(Y) = H(Y_{Gauss}) - H(Y)
\] (11)

When \(Y\) has a Gaussian distribution, \(N_y(Y) = 0\). The stronger the non-Gaussianness of \(Y\), the larger the value, Therefore, it can be used as an evaluation estimate of the non-Gaussianness of random variables. Equation (12) needs to calculate the probability density distribution function when calculating the differential entropy, which is difficult to achieve in practical applications, so we can use the following equation for approximate calculation:

\[
N_y(Y) = [E(g(Y)) - E(g(Y_{Gauss}))]^2
\] (12)

Observe the matrix \(X\), and use the FastICA algorithm to find the unmixing matrix \(W\) to \(N_y(W^TX)\) have the largest Gaussian non-Gaussian property. The approximate Newton iteration formula of the unmixing matrix \(W\) is:

\[
\begin{align*}
W^* &= E(Xg(W^TX)) - E(Xg'(W^TX))W \\
W &= W^* / ||W^*||
\end{align*}
\] (13)

The second step is the selection of non-linear function \(g_m\):

\[
g_m(s) = \begin{cases} 
\exp(-q(s) | s |) & \hat{\mu}_{ik} > 3 \\
\text{sign}(s) & \hat{\mu}_{ik} \leq 3 \\
\text{sign}(s) & |s| \leq 1.8
\end{cases}
\] (14)

The third step of separation signal purification and adjustment can be specifically divided into two steps B1 and B2.

B1: make \(\hat{W}^{STM} = [\hat{W}_1^{STM}, \ldots, \hat{W}_d^{STM}]\), \(\hat{W}^{STM} = [\hat{W}_1^{STM}, \ldots, \hat{W}_d^{STM}]\). These values can be calculated by the FastICA algorithm in the first step. Next, perform a fourth-order matrix estimation for the initial separation signal obtained in the first step, according to \(\hat{U}_k\) Estimate the value of each source signal, and then determine different nonlinear functions based on this value.
Let $k=1, 2 \ldots d$, initial $\hat{W}_k = \hat{W}_k^{SYM}$, after completion, judge $|\hat{W}_k^+\hat{W}_k^{SYM}| \geq 0.95$, if the value is greater than or equal to 0.95, proceed to the next iteration:

$$\hat{W}_k^+ = Zg_s(\hat{W}_k Z) - \hat{W}_k g_s(\hat{W}_k Z)_{N}$$

$$\hat{W}_k = \hat{W}_k^+ / ||\hat{W}_k||$$  \hspace{1cm} (15)

Repeat the above iterations until the result is convergence. In case $|\hat{W}_k^+\hat{W}_k^{SYM}| < 0.95$, then the estimated $\hat{W}_k^+$ and $\hat{W}_k^{SYM}$, There is a big difference, so keep $\hat{W}_k^+ = \hat{W}_k^{SYM}$, And make $g_k(s) = \tanh(s)$.

B2: When $k=1, 2 \ldots d$, the following parameters should be calculated

$$\tilde{\mu}_k = \mu_k^i g_i^s(\mu_k) / N$$

$$\tilde{\tau}_k = |\tilde{\mu}_k - \tilde{\tau}_k|$$

$$\tilde{\beta}_k = \tilde{\gamma}_k g_k^s(\tilde{\mu}_k) / N$$

$$\tilde{y}_k = \tilde{\beta}_k - \tilde{\mu}_k^2$$

$$c_{k,i} = \begin{cases} \tilde{\tau}_k \tilde{\tau}_i \text{ when } 1 \neq k \\ 1 \text{ when } 1=k \end{cases}$$

$\hat{W}_k = \text{diag}(c_{k}, \ldots, c_{d}) \hat{W}_k^+$

$$\hat{W}_k^{aux} = (\hat{W}_k^+)^{-1/2} \hat{W}_k^+$$  \hspace{1cm} (18)

$$\hat{W}_k^{REF} = (\hat{W}_k^{aux})_{k}$$  \hspace{1cm} (19)

$$\hat{W}_ {REF} = [\hat{W}_1^{REF}, \ldots, \hat{W}_d^{REF}]^T$$  \hspace{1cm} (20)

In the above calculation, $Z$ represents the mixed signal after whitening, $Z = \tilde{C}^{-1/2}(X - \bar{X})$, $C$ represents the covariance matrix of the sample, $\tilde{C} = (X - \bar{X})(X - \bar{X})^T / N$, $\bar{X}$ represents the sample mean of the mixed data, $\hat{u}_k = (\hat{W}_k^{SYM})^TW$ , $\hat{u}_k = E[s_k g(s_k)]$, $\hat{\mu}_k = E[g^s(s_k)]$, $\hat{\beta}_k = E[g^s(s_k)]$.

4. Simulation results and analysis

The two signals with the same frequency received by the antenna at the receiving end have the same symbol period $T$, and the symbol period $T=16$; $0 \leq \tau_1(t), \tau_2(t) < T$ is the time delay between the local reference clock and the received signal. Different amplitude fading $h_1(t)$, $h_2(t)$, the value of the amplitude $A_1=A_2=1$. With the same local carrier frequency $w_0$, the carrier frequency offsets of the two modulated signals are $w_1$ and $w_2$. Different initial phases $\phi_1 = 1$, $\phi_2 = 2$, are selected as, respectively.

We conducted simulation experiments on the improved EFICA algorithm proposed in this paper and the EFICA algorithm at the same time. In the experiment, two signals with the same frequency are selected, a noise signal is randomly generated, and the three signals are mixed to separate the mixed signals.
In order to improve the performance of the source signal, it is necessary to perform whitening before data separation. The input observation vectors after the whitening process are no longer relevant. Although correlation is a weaker statistical attribute than independence, whitening can simplify the source signal separation algorithm and make the iterative process simpler.

The improved EFICA algorithm selects the online mode to whiten the signal. From the eigenvalue decomposition (EVD) of the covariance matrix of the mixed source $x$, we know: $R_x = E \Lambda E^T$. Where $E$ is an orthogonal matrix with columns formed by the eigenvectors of $R_x$, it is a diagonal matrix with the eigenvalues of $R_x$ as the diagonal. If set $V = \Lambda^{-1/2} E^T$, then there are $E [pp^T] = VE \Lambda \text{Cov} E^T = \Lambda^{-1/2} E^T \Lambda E \Lambda^{-1/2} = I$, the matrix $V$ is not unique, because for any orthogonal matrix $U$, $UV$ is also a whitening matrix.

Use the EFICA algorithm and the improved EFICA algorithm to separate the mixed signal at the same time. Through the separation results, compare whether the improved EFICA algorithm has better separation effect than the EFICA algorithm.
Figure 5 EFICA algorithm separation

Figure 6 EFICA improved algorithm separation

Through the separation results, we can clearly see that the improved EFICA algorithm is closer to the source signal, whether in amplitude or phase, and the improved EFICA algorithm has a better separation effect. In order to better compare and improve the separation performance of the algorithms, the average correlation coefficient and crosstalk error of the source signal and the separated signals of the two algorithms are selected as the measure of the separation effect. Use 10 consecutive experiments for measurement.

Table 1 Separation time of 2 algorithms, average correlation coefficient and crosstalk error

| Algorithm       | Time/s  | Average correlation coefficient | Crosstalk error |
|-----------------|---------|--------------------------------|-----------------|
| EFICA algorithm | 0.029470| 0.9972                         | 9.2896          |
| EFICA improved  | 0.031328| 0.9975                         | 9.0329          |

It can be seen from Table 1 that although the steps of the improved algorithm are increased, it has little effect on the speed of the algorithm. From the average correlation coefficient and crosstalk error, it can be seen that the average correlation coefficient of the improved EFICA algorithm is higher than that of the EFICA algorithm, and the crosstalk error is lower than that of the original EFICA algorithm.
Figure 8 Crosstalk error between EFICA algorithm and its improved EFICA algorithm

It can be seen from Figure 7 and Figure 8 that the average correlation coefficient and crosstalk error of the improved EFICA algorithm are more stable than those of the EFICA algorithm. Actual calculations show that the average crosstalk error of the improved EFICA algorithm is 9.14808 and the variance is 0.0086. The average crosstalk error of the EFICA algorithm is 9.94516, and the variance is 0.7408. The improved EFICA algorithm is better than the EFIC algorithm in terms of separation effect and stability.

5. Conclusion
This paper focuses on the separation of signals at the same frequency, and proposes signal separation based on the improved EFICA algorithm. By comparing the separation results with the EFCA algorithm, a communication mixed signal experiment is carried out on the Matlab platform. Experiments show that the algorithm is compared with the EFICA algorithm. Compared with the case where the running time is not much different, the improved EFICA algorithm can increase the average correlation coefficient of the algorithm, reduce the crosstalk error of the algorithm, improve the stability of the EFICA algorithm. Use the improved EFICA algorithm to separate the same frequency mixed signal, which has a better separation effect. Therefore, the improved EFICA algorithm will have a broader application prospect.

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