TEST Engineering & Management

July-August 2020
ISSN: 0193-4120 Page No. 861 - 869

Multi User Detection Based on Independent Component Analysis and Compressed Sensing

Cheng Ying[1], Lu Xiaojun[2], Zhou Yuanyuan[1,*], Fang Chenghua[1]
1School of Electronic Information Engineering, Hefei Normal University, Anhui Hefei 230601,.China
2Information Centre, Hefei Municipal Public Security Bureau, Anhui Hefei 230041, China
Corresponding Author's Email: yyzhou@hfnu.edu.cn

Article Info
Volume 83
Page Number: 574 - 585
Publication Issue:
July-August 2020

Article History
Article Received: *06 June 2020*
Revised: *29 June 2020*
Accepted: *14 July 2020*
Publication: *25 July 2020*

Abstract

In the process of wireless communication, the improved wireless communication technology is optimized by exploiting the sparsity of the signal transmission to improve the system communication efficiency and the communication performance. In the case of insufficient system resources and few active users, in order to save system resources, the pilot signal is not sent. Recover the source signal from the received data when the channel parameters are unknown., we combine the advantages of independent component analysis and compressed sensing to obtain the multiuser detection. Based on the multi-user detection model, the independent component analysis algorithm is introduced into the compressed sensing data processing. Two different data processing processes are analyzed and compared. The experimental results show that the compressive sensing algorithm combined with the independent component analysis can be applied to multi-user detection without prior information and has good performance.

Keywords: *Independent component analysis, compressive sensing, Multiuser detection*

1. Introduction

In the process of multiuser transmission detection, only a few users transmit signals at the same time, so the transmission signal is sparsely. In the process of wireless communication, by exploiting this sparsity to optimize and improve wireless communication technology, we can effectively improve the efficiency of system communication and improve the performance of the system. Compressed sensing is applied to multiuser detection[1-3]. Compressed sensing has a strong ability to sparse signal, but in the process of sparsity, it often omits some components of weak signals. And the independent component analysis can reveal all kinds of signals in a relatively comprehensive way. But the excessive density of the independent component reduces the ability to analyze the effective signal [4-6]. Therefore, it is better to combine the advantages of the two theories to carry out multiuser detection.

2. System signal model

In the multiuser detection of uplink, if the user uses code division multiple access, each user is assigned a single sequence of L length, each user has its own sequence information, and the base station has the sequence information of all users. The multiuser detection signal model in the uplink can be expressed as

$$Y = Hdiag(s)V + N \tag{1}$$

The above model indicates that there are n users in a cell. The length of the spread code for each user is l . $H \in C^{m\times n}$ is a channel transfer matrix, and $s \in \{0,1\}^{n\times 1}$ represents the user information vector. When the user i has transmission data, the value of the corresponding element is $s_i = 1$. When the user is in idle state, the value of the corresponding element

July-August 2020
ISSN: 0193-4120 Page No. 861 - 869

is $s_i = 0$. Each line of the $V \in C^{n \times l}$ corresponds to the only spread sequence information of a user. Multiuser detection is to restore the vector s. N represents the white noise component. The above equation can be expressed as

$$Y = H(diag(s)V) + N = HV^{'} + N \qquad (2)$$

When $l = 1$, The above problem is a general compressive perception problem model. In traditional multiuser detection, all users are activated. When the base station's antenna number m is much smaller than the number of users n. And when $n = 1$, it is impossible to recover the determined coefficient vector s. Therefore, in the real system, CDMA, FDMA and TDMA are needed to distinguish users[7-9]. Take CDMA, for example, which assigns a unique identifier to each user, and $l > n$. In the detection process, which user is in the activation state is unknown, so the detection is to treat all users as activated state. Each user's codeword is used to match the received data at the receiving end. The amount of work and cost is huge. Only a small number of users in the uplink are transmitting data at the same time, so the transmission signal at the same time is sparsely. Using this sparsity, compression perception can be effectively applied.

In the uplink channel estimation, the terminal sends a specific pilot sequence to the base station for the base station to perform channel estimation. The base station knows the pilot sequence of each user. At this point, the channel response corresponding to the transmitted pilot sequence user needs to be restored.

$$Y^T = V^T diag(s) H^T + N^T = V^T H^{'} + N^T \qquad (3)$$

In the above expression, $H^{'}$ is the row sparse matrix $diag(s)H^T$ that needs to be restored. From the above analysis, it can be seen that the signal model can be expressed as formula (2) (3) for the uplink multiuser detection or uplink channel estimation, only the variables to be solved are different.

In the multiuser detection model, compared with the compressed sensing model, it is to recover $diag(s)V$. We consider a signal $x \in R^n$ with sparse s, and by using compressed sensing technology, measurement vector $y \in R^m$ can be obtained from the signal and the n dimensional space through matrix $A \in R^{m \times n}$.

$$y = Ax + N \qquad (4)$$

The research shows that when the measurement matrix A is gaussian random matrix or Bernoulli random matrix, the sparse vector can be well recovered by compressed sensing. When the number of rows of the measurement matrix satisfies $m \sim O(cs \log n / s)$, where c is the coefficient related to the probability of recovery success, s is the sparsity of the signal, and n is the dimension of the signal vector. When the above conditions are not satisfied, and m is even smaller than this, it is impossible to directly use compressed sensing technology to restore the original sparse signal. In order to solve this problem, the constraint of compressed perception can be satisfied by dimensional extension. It is usually assumed that the base station has m receiving antennas, and the number of observations is m. m is far less than n and can't restore S. In literature [10], an extended dimension is proposed to meet the requirements of the compressed sensing algorithm. Assuming that the extended dimension is d,

$$Y_1 = Adiag(x_1, x_2, ..., x_n)V + N \qquad (5)$$

$V \in R^{n \times d}$ is a dimension extension matrix, $V = [v_1, v_2, ..., v_n]^T$, among this $v_i \in R^d$ is the spread spectrum vector of user i. $Y_1 \in R^{d \times m}$ represents the matrix measured by the result. The above equation can be expressed as

$$Y_1^T = V^T diag(x_1, x_2, ..., x_n) A^T + Z^T = V^T X_A + N^T \qquad (6)$$

$$X_A = diag(x_1, x_2, ..., x_n) A^T \qquad (7)$$

In an expression $Y_1^T \in R^{d \times m}$. $X_A \in R^{n \times m}$ is the row sparse matrix. In equation (7), the recovery process of sparse matrix X_A can be a compression perception problem of MMV. By dimensional extension, the signal model that could not be used

July-August 2020
ISSN: 0193-4120 Page No. 861 - 869

for compressed sensing was transformed into a model that could be used for compressed sensing. When X_A restored correctly, the non-zero elements of the original sparse signal x measured by the matrix A can be expressed as

$$\hat{x}_i = \frac{X_A(i)A^T(i)}{\|A^T(i)\|_2^2} \quad (8)$$

The dimension expansion matrix V is the Gauss matrix. After dimension expansion, the recovery process of sparse matrix becomes an MMV compression perception problem. SOMP algorithm can be used to restore the sparse signal and realize the result of multiuser detection.

Usually, in wireless communication, the pilot sequence is used to estimate channel parameters in order to obtain channel parameter information. On many occasions, such as wireless sensor networks, the number of sensors that usually transmits data is not much, and the wireless resources are not rich, so in order to save the system resources, the source data recovery situation is considered without the need of pilot information and the unknown channel parameters.

3. Multiuser detection based on CSICA1

In the theory of compressed sensing, the source signal S can be expressed sparsely in a group of bases：

$$S = \sum_{i=1}^{N} \psi_i \alpha_i = \Psi\alpha \quad (9)$$

In the formula: $\Psi = [\psi_1, \psi_2, ..., \psi_M]$ is the base vector, α is the coefficient vector. For a given observation signal X and a measurement matrix Φ, the source signal is S found.

$$X = \Phi\Psi\alpha \quad (10)$$

In the compressed sensing algorithm, it is known that the measurement matrix Φ is known, and it is designed as a random matrix. The coefficient base Ψ is also known. In this premise, a variety of optimization algorithms are designed to estimate the sparse representation of the signal α. Then the source signal $S = \Psi\alpha$ is obtained by transformation.

Independent component analysis (ICA) is a blind source separation technique [11,12], which extracts independent components from mixed signals. The mathematical model is as follows:

$$X = AS \quad (11)$$

X is a set of vectors $[x_1, x_2, \cdots, x_n]^T$. $x_i, i = 1\cdots n$ is a group of n different observation data. S is a set of source vectors $[s_1, s_2, \cdots, s_m]^T$ $s_i, i = 1\cdots m$ is an independent source signal, and A is a $n \times m$ dimensional full rank mixed matrix. The purpose of ICA is to get the separation matrix W through certain rules in the case of only known observation data X. $\hat{S} = WX$ is the approximate estimation of the source vector S. But the premise that the signal source can be separated is that the dimension of the observed data n is greater than the number of the source signals m, and there is only one Gauss signal in the source signal. The widely used ICA algorithm is the Fast ICA algorithm. The independent component analysis algorithm is used for signal extraction. Combined with the signal processing process of compressed sensing, the recovery process of source signal is as follows.

Fig.-1 is a formation block diagram of observation data. The data extraction process of compressed sensing is the process of extracting information from the observed values of the mixed signal X. The source signals $S = [s_1(t), ..., s_n(t)]$ are mixed in the channel transmission process by the mixed parameter matrix A to get the mixed signal $X = [x_1(t), ..., x_n(t)]$. The observation matrix is Φ. The compressive observation value is $Y = [y_1, ..., y_n]$.

$$Y = \Phi S^T A^T \quad (12)$$

July-August 2020
ISSN: 0193-4120 Page No. 861 - 869

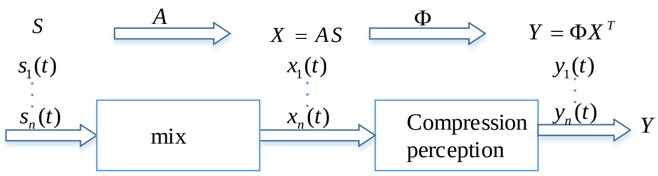

Figure. 1. Formation block diagram of observation data

Fig.-2 is a traditional processing framework for information extraction from observed values of mixed signal compression. $\hat{s}_i(t)$、$\hat{x}_i(t)$ and $\hat{A}$ is Valuation of $s_i(t)$、$x_i(t)$ and A respectively. In order to extract the mixed parameters and source signals. The mixed signal $\hat{X}$ is reconstructed first and the mixed parameter $\hat{A}$ and the source signal $\hat{S}$ are extracted.

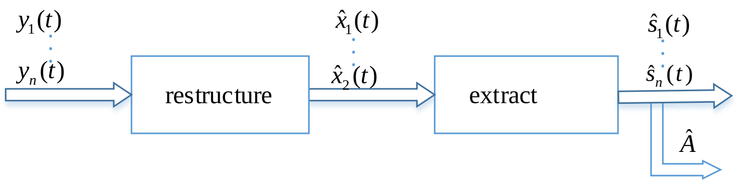

Figure. 2. The process of extracting data of CSICA1

In Fig.-2, SOMP can be used to reconstruct the mixed parameters. The specific implementation is as follows:

Step1: initialization residual error $R_0 = Y$, support set $\Lambda_0 = \phi$, iteration times $t = 1$, $\hat{T}$ is the null matrix;

Step2: matching: find the atom that best matches the current residual error

$$\lambda_t = \arg\max_{i=1,\dots,N} \left\| R_{t-1}^T \theta_i \right\|_1$$

Step3:update the support set

$$\Lambda_t = \Lambda_{t-1} \cup \lambda_t$$

Step4: estimate the sparse signal

$$\hat{T}_t = \arg\min_{\alpha} \left\| Y - \Theta_{\Lambda t} T \right\|_2$$

Step5:update residual

$$R_t = Y - \Theta_{\Lambda t} \hat{T}_t$$

Step6:t=t+1, if $t \le K$, return step 2, otherwise the algorithm will end.

Step7:The location of nonzero rows in $\hat{T}$ is stored in Λ_t and $\hat{T}_{\Lambda t} = \hat{T}_t$.

The signal $\hat{x}_i(t)$ is obtained through the above process, and the desired mixed parameter matrix $\hat{A}$ and source signal $\hat{s}_i(t)$ are recovered from $\hat{x}_i(t)$. Comparing the model (6) with the model (12), it can be seen that the above data processing process can be applied to the multiuser detection process. We set the multiuser detection in the scenario of sporadic communication, and use CDMA as a multi-access mode, channel parameters are unknown, using the above process to detect, the results are recorded as CSICA1.

4. Multiuser detection based on CSICA2

In wireless channels, we focus on mixed parameters, which is the channel parameters, not mixed signals. In the process of signal detection, the channel parameters need to be estimated by pilot signal, and the system resource cost is high. In order to improve the recovery accuracy of the source signal and obtain channel parameters directly in the receiving signal to reduce the system overhead, we change the signal recovery and extraction process.

Reanalyze the compression mixing model shown in equation (11), make

July-August 2020
ISSN: 0193-4120 Page No. 861 - 869

$$G = \Phi S^T \tag{13}$$

The ith column $g_i(t) = \Phi s_i(t)^T$ of the matrix G is the observation value of source signal s_i after compressed observation by observation matrix Φ. so

$$Y = GA^T \tag{14}$$

At this time

$$y_i = \Phi x_i(t) = \sum_{j=1}^{n} a_{ji}\Phi s_j(t) = \sum_{j=1}^{n} a_{ji} g_i(t) \tag{15}$$

The compressed sensing algorithm is to reconstruct the mixed matrix X and then extract the source signal S on the premise of the known observation signal matrix Y, the measurement matrix Φ and the sparse matrix Ψ. Mixed signals are usually only an intermediate variable for solving mixed or source signals. If we can bypass the intermediate variable and solve the variable of interest directly, it will greatly simplify the work.

The literature [13] proposed ICA algorithm with compressed sensing to get another data processing process. The process is shown as shown in Fig.-3. In Fig.-3 the ICA algorithm is used to extract the mixed matrix A and the compressing observation matrix of source signal G, without the need to reconstruct the mixed signal X. In order to distinguish from the data processing in Fig.-2, we refer to the processing of Fig.-3 as CSICA2.

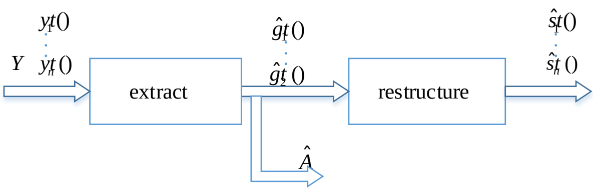

Figure. 3. The process of extracting data of CSICA2

Because no reconstruction process is needed, the algorithm can not only reduce the complexity of the algorithm when extracting the mixed matrix, but also reduce the error introduced by the reconstruction algorithm when reconstructing the mixed signal.

Through the above steps, we can get the mixed parameter matrix A in advance and get the source signal $\hat{s}_i(t)$ from $\hat{g}_i(t)$. Unlike the processing in Fig.-2, we avoid the extraction of the intermediate variable $\hat{X}$, thus avoiding the accumulation of data errors. Therefore, in theory, the accuracy of data processing in Fig.-3 should be better than that in Fig.-2.

In order to improve the accuracy of data processing, observation model (11) and model (6), we found that ICA data processing ignored the impact of noise. As we know from model analysis of ICA, the separation matrix is obtained under the noise-free model. Therefore, the algorithms of ICA usually ignore the noise, but the noise exists, which leads to the estimation deviation of the algorithm. Considering the influence of noise, the algorithm of independent component analysis is modified [14]. The noise model of ICA is as follows

$$X(t) = AS(t) + N(t) \tag{16}$$

Above $X(t)$ is the observation data, $S(t)$ is the source signal, A is the mixed matrix, $N(t)$ is the gaussian white noise component. Each source signal is statistically independent from each other, and is independent from each independent component of the noise. Ignoring the noise, the covariance of observed data is as follows:

$$\begin{aligned} C &= E\left\{AS(t)\left(AS(t)\right)^T\right\} = E\left\{AS(t)S(t)^T A^T\right\} \\ &= AE\left\{S(t)S(t)^T\right\}A^T = AIA^T = AA^T \end{aligned} \tag{17}$$

Considering noise, the covariance of observed data is as follows:

$$\begin{aligned} \Gamma &= E\left\{X(t)X(t)^T\right\} = E\left\{\left(AS(t)+N\right)\left(AS(t)+N\right)^T\right\} \\ &= E\left\{AS(t)(AS(t))^T\right\} + E\left\{NN^T\right\} \\ &= C + \sigma^2 I \\ &= C + \psi \end{aligned} \tag{18}$$

From the above formula, it can be seen that the covariance of the observed data with noise is the sum of the covariance of the observed data without noise and the covariance of the noise. It can be seen from the moment analysis theory

$$C = U\Lambda U^T \tag{19}$$

$$\Gamma = U_1 \Lambda_1 U_1^T \quad (20)$$

Where U and U_1 are the eigenvector matrix of C and Γ respectively, Λ and Λ_1 are the matrix formed by the eigenvalues of C and Γ respectively. Observation formula (1) (2), $\Gamma - C = \sigma^2 I$, so

$$\begin{aligned} &\Lambda_1 = \Lambda + \sigma^2 I \\ &U = U_1 \end{aligned} \quad (21)$$

If the noise data is processed according to the general independent component analysis algorithm based on the noise-free model, the deviation will occur during the pretreatment of albinism. Set the whitened data Z

$$Z = \Lambda_1^{-1/2} U^T X \quad (22)$$

although $E\{ZZ^T\} = I$, Meet the requirement of data whitening. But for the mixed data that we are interested in, the whitening process is not as whitening as we think.

$$\begin{aligned} &COV\{\Lambda_1^{-1/2} U^T AS(t)\} \\ &= E\left\{\Lambda_1^{-1/2} U^T AS(t)\left(\Lambda_1^{-1/2} U^T AS(t)\right)^T\right\} \\ &= \Lambda_1^{-1/2} U^T E\{AS(t)S(t)^T A^T\} U \Lambda_1^{-1/2} \\ &= \Lambda_1^{-1/2} U^T C U \Lambda_1^{-1/2} \\ &= \Lambda_1^{-1/2} U^T U \Lambda U^T U \Lambda_1^{-1/2} \\ &= \Lambda_1^{-1/2} \Lambda \Lambda_1^{-1/2} \neq I \end{aligned} \quad (23)$$

Albinism is changed as follows

$$Z = (\Lambda_1 - \sigma^2 I)^{-1/2} U_1^T X \quad (24)$$

Although the whitening process of equation (4.18) has whitened the mixed data of interest $AS(t)$, the processed data Z is not satisfied $E\{ZZ^T\} = I$. Therefore, this treatment is also called equation (4.18), which is semi-bleaching treatment. In order to simplify the derivation, let $V = (\Lambda_1 - \sigma^2 I)^{-1/2}$, so

$$\begin{aligned} &E\{ZZ^T\} \\ &= E\left\{VU_1^T X\left(VU_1^T X\right)^T\right\} = VU_1^T E\{XX^T\} U_1 V^T \\ &= VU_1^T (C + \psi) U_1 V = VU_1^T C U_1 V + VU_1^T \psi U_1 V \end{aligned} \quad (25)$$

The first half of the above equation is the value after the mixed data is whitened, and the second half is the value of the noise component. According to equation (4.15), we can get:

$$\begin{aligned} &VU_1^T C U_1 V = (\Lambda_1 - \sigma^2 I)^{-1/2} U_1^T U \Lambda U_1^T U (\Lambda_1 - \sigma^2 I)^{-1/2} \\ &= (\Lambda_1 - \sigma^2 I)^{-1/2} \Lambda (\Lambda_1 - \sigma^2 I)^{-1/2} = \Lambda^{-1/2} \Lambda \Lambda^{-1/2} = I \end{aligned} \quad (26)$$

so

$$\begin{aligned} &E\{ZZ^T\} = I + VU_1^T \psi U_1 V \\ &= I + (\Lambda_1 - \sigma^2 I)^{-1/2} U_1^T U \sigma^2 I U_1^T U (\Lambda_1 - \sigma^2 I)^{-1/2} \\ &= I + \sigma^2 (\Lambda_1 - \sigma^2 I) \end{aligned} \quad (27)$$

let $T = I + \sigma^2 (\Lambda_1 - \sigma^2 I)$,The iterative formula of noise independent component analysis is obtained after correction

$$w_{i,k+1} = T^{-1} E\left\{Zg\left(w_{i,k}{}^T Z\right)\right\} - 3 * E\left\{g'(w_{i,k}{}^T Z)\right\} w_{i,k} \quad (28)$$

After each iteration, the normalization formula of the vector is

$$w_{i,k+1} = w_{i,k+1} \Big/ \sqrt{w_{i,k+1}{}' T w_{i,k+1}} \quad (29)$$

The concrete realization is as follows:

Step1: Y is centralated and whitened to get $Z = (\Lambda_1 - \sigma^2 I)^{-1/2} U_1^T X$;

Step2: $i = 1$;

Step3:The i column w_i of the initialization matrix W , the element is a random value, the modulus is 1;

Step4: $w_{i,k+1} = T^{-1} E\left\{Zg\left(w_{i,k}{}^T Z\right)\right\} - 3 * E\left\{g'(w_{i,k}{}^T Z)\right\} w_{i,k}$;

Step5:Orthogonalization of w_i ,

$w_i \leftarrow w_i - \sum_{j=1}^{i-1} (w_i^T w_j) w_j$;

July-August 2020
ISSN: 0193-4120 Page No. 3672 - 3680

Step6: Normalization： $w_{i,k+1} = w_{i,k+1} / \sqrt{w_{i,k+1}{}'Tw_{i,k+1}}$;

Step7: Judge whether the w_i is convergent and the non convergence returns to the step 4;

Step8: $i \leftarrow i+1$, if $i \le n$, returns to the step 3;

Step9: $\hat{A} = W^{-1}, \hat{G} = (ZW^{-1})^T$

The above process can get the parameter matrix A and the observed value of the source signal G. Then use the OMP algorithm to restore the source signal S. Combining the data processing in Figure 3 with the Fast ICA algorithm considering the noise model, we obtain a multiuser detection process called CSICA2.

5. Simulation result

Fig.-4 simulation environment is an additive Gauss white noise channel. The results compare the performance of three different detection methods under different signal to noise ratio. The three methods are MMSE, CSICA1 and CSICA2, respectively. In the simulation, the total number of users is 128. The extended dimension is 10. The activation user is 6. It can be seen that under the condition of low signal to noise ratio, MMSE is superior to the other two methods. However, as the signal to noise ratio increases, the performance of CSICA1 and CSICA2 is rapidly improved. The performance of CSICA2 has been better than CSICA1 because of the reduction of the refactoring step and the increase of the anti noise ability.

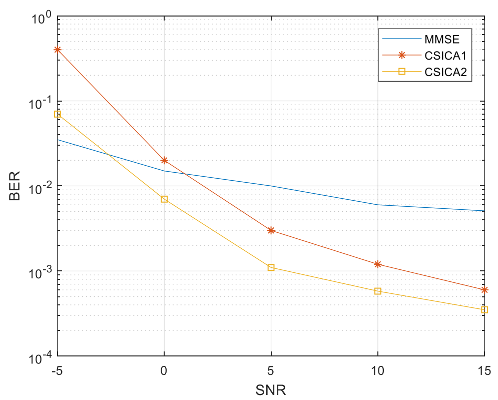

Figure. 4. Bit error rate under different SNR

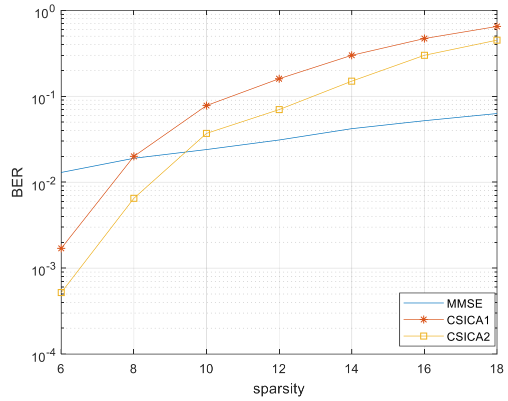

Figure. 5. Bit error rate under different Sparsity

Fig.-5 the simulation environment is still in the additive Gauss white noise channel. But the signal to noise ratio is fixed in 10dB. The results compare the performance of three detection methods under the different sparsity. In the simulation, if the total number of users is 128, the extended dimension is 10. It can be seen that with the increase of sparsity, the performance degradation of CSICA1 and CSICA2 are both serious. This phenomenon is due to the increasing number of active users, increasing sparsity, compressed sensing algorithm of the correct recovery probability decreased. But comparing the two algorithms, the performance of CSICA2 is better than that of CSICA1 with the increase of active users. This is mainly due to the accumulation of errors in the process of data processing. in addition, the impact of ICA algorithm noise is also the reason for the impact of the results.

6. Conclusion

In wireless sensor network scenarios, the sensor state is not a continuous transmission of information, occasionally in the transmission state. The active state of sensors is controlled by time and event driven. In this kind of sporadic wireless communication state, we consider using CDMA as multiple access mode, without sending any prior information, when the channel information is unknown, the system uses the received data to transmit the signal or obtain the channel information.

July-August 2020
ISSN: 0193-4120 Page No. 3672 - 3680

Information acquisition is processed by combining compressed sensing and independent component analysis. In this paper, two data processing schemes are discussed, one of which is to obtain mixed signals first, and then separate the source signal and mixed parameters by independent component analysis. The other is to separate the mixed parameter and the observed value of the source signal directly by independent component analysis, and then recover the source signal from the observed value. Experimental results show that the two data processing processes can be used in the case of sporadic wireless communication, and the detection performance is better. But the second scheme has better performance, so the second scheme can be used as the first choice for multiuser detection in wireless communication without channel prior information. In order to further improve the detection performance, considering the influence of noise, the influence caused by noise is reduced in the process of independent component analysis (ICA) of the second scheme, and whitening and iterative processing are modified from the noise model.

7. Acknowledgements

The authors would like to thank Natural science research project of the Anhui Education University (KJ2018A0490), Natural science research project of the Anhui Education University (KJ2017A923), Key projects of Anhui province universities outstanding young talents support program (gxyqZD2016233), Opening Foundation of Institute of BWDSP Industrialization (2017DSP01) for financial support.

8. References

[1] Du Y, Dong B, Chen Z, et al. Efficient Multi-User Detection for Uplink Grant-Free NOMA: Prior-Information Aided Adaptive Compressive Sensing Perspective[J]. IEEE Journal on Selected Areas in Communications, 2017, PP(99):1-1.

[2] Ji Y, Bockelmann C, Dekorsy A. Numerical analysis for joint PHY and MAC perspective of Compressive Sensing Multi-User Detection with coded random access[C]// IEEE International Conference on Communications Workshops. IEEE, 2017:1018-1023.

[3] Du Y, Dong B, Chen Z, et al. Efficient Multi-User Detection for Uplink Grant-Free NOMA: Prior-Information Aided Adaptive Compressive Sensing Perspective[J]. IEEE Journal on Selected Areas in Communications, 2017, PP(99):1-1.

[4] Kamathe R S, Joshi K R. A novel method based on independent component analysis for brain MR image tissue classification into CSF, WM and GM for atrophy detection in Alzheimer's disease[J]. Biomedical Signal Processing & Control, 2018, 40:41-48.

[5] Tugnait J K. On Detection and Mitigation of Reused Pilots in Massive MIMO Systems[J]. IEEE Transactions on Communications, 2018, 66(2):688-699.

[6] Kamathe R S, Joshi K R. A novel method based on independent component analysis for brain MR image tissue classification into CSF, WM and GM for atrophy detection in Alzheimer's disease[J]. Biomedical Signal Processing & Control, 2018, 40:41-48.

[7] Pelletier B, Champagne B. Group-Based Space-Time Multiuser Detection with User Sharing[J]. IEEE Transactions on Wireless Communications, 2018, 6(6):2034-2039.

[8] Du Y, Dong B, Zhu W, et al. Joint Channel Estimation and Multiuser Detection for Uplink Grant-Free NOMA[J]. IEEE Wireless Communications Letters, 2018, PP(99):1-1.

[9] Benkrinah S, Benslama M. Acquisition of PN sequences using multilayer perceptron neural network adaptive processor for multiuser detection in spread‐spectrum communication systems[J]. International Journal of Numerical Modelling Electronic Networks Devices & Fields, 2018, 31(1):e2265.

[10] Wei Lu, DeshengWang, Yingzhuang Liu, Fan Jin. Compressed Sensing via Dimension Spread in Dimension Restricted Systems. Wireless Personal Communication. 2013 (71):2625–2636.

[11] Aapo Hyv¨arinen, Juha Karhunen, Erkki Oja. Independent Component Analysis[M]. New York. John Wiley & Sons, Inc. 2001.

[12] Hyvarinen A, Oja E. Independent Component Analysis: Algorithms and Applications [J]. Neural Network, 2000, 13(4): 411-430.

[13] Hongwei Xu, Ning Fu, Congru Yin, Liyan Qiao, Xiyuan Peng. "Blind Separation of

July-August 2020
ISSN: 0193-4120 Page No. 3672 - 3680

Sufficiently Sparse Sources in Multichannel Compressed Sensing". 19th International Conference on Digital Signal Processing (DSP).HongKong, China. August, 2014. 515-520.
[14] He H L, Wang T Y, Leng Y G, et al. Noisy ICA based on cascaded bistable stochastic resonance denoising[J]. Journal of Tianjin University, 2006, 60(60):163.