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Blind Spectrum Reconstruction algorithm based on distributed Modulation broadband Converter

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Abstract

Distributed modulation wideband converter (DMWC) is a network system developed from the modulation wideband converter (MWC). Common reconstruction algorithms need to know the signal sparsity in advance, but the actual electromagnetic environment sparsity is difficult to predict. Therefore, this paper proposes an improved SAMP (SwSAMP) algorithm to achieve DMWC blind spectrum reconstruction. In the case of unknown signal sparsity, weak selection method is adopted to improve the accuracy of the support set, and the combination of size and step is adopted to rapidly approximate and improve the efficiency of the algorithm. The simulation results show that the SwSAMP algorithm can improve the tolerance of DMWC to attenuation, and can improve signal sparsity, reduce the number of nodes, and reduces the overhead of DMWC hardware.

Keywords

Distributed Modulation wideband Converter (DMWC); Adaptive sparsity; Support set.

1. Introduction

With the development of wireless communication technology, the demand for bandwidth in the field of signal processing gradually increases, and the contradiction between spectrum resources becomes more intense [1]. In order to make effective use of the spectrum, scholars are committed to the study of electromagnetic spectrum sensing technology, whose purpose is to find and use the occupied holes in the electromagnetic spectrum [2], and corresponding results have been achieved [3,4]. According to the traditional Nyquist Sampling law, when Sampling wideband signals, the analog converter will face great pressure, and the emergence of CS (Compressed Sensing) [5] promotes the development of signal undersampling technology. Among them, the most typical sampling system is MWC (Modulated Wideband Converter) [6,7], which realizes the compression sampling of broadband signals through hardware, making the spectrum sensing undersampling technology more mature. At present, radar [8], signal parameter estimation [9,10], Cognitive radio spectrum sensing [11,12] and other fields have also been widely applied to MWC systems. As MWC does not have Distributed characteristics in electromagnetic environment, DMWC (Distributed Modulated Wideband Converter) system was proposed [13]. It combines the idea of CS and Wireless Sensor Networks (WSN), and takes each SU in a different position in WSN as a Distributed Sense Node (DSN), and each Node independently completes the under-sampling task. At the same time, signal transmission attenuation and receiving phase difference between nodes are introduced, and each node sends the sampled data to the Fusion Center (FC) for signal spectrum reconstruction in FC. DMWC solves the problems such as multipath fading, shadow and time-varying support set faced by a single MWC in the real CR environment, which has certain value and significance in the field of electromagnetic spectrum sensing in the future.

Among the existing algorithms, OMP algorithm is widely used, but it needs to predict signal sparsity. For this, this article is based on blind refactoring SAMP algorithm was improved,

instead it is presented that an algorithm suitable for DWMC SwSAMP, weak choice way of choice, choice is greater than a certain threshold of atoms, and improve the atom selection accuracy, algorithm is an iterative process using step small step for a combination of long, can more quickly and efficiently approximate signal sparse, the experimental results show that This algorithm can improve the blind spectrum perception performance of DMWC.

2. DMWC spectrum analysis and reconstruction algorithm

2.1. Distributed modulation broadband converter theory

2.1.1. DMWC system model

As shown in Figure 1, the whole sensing system includes: a signal source X (t), M sensing nodes and a data processing center. Each node is equivalent to a sampling channel of MWC, independently performs under-sampling task, and finally completes signal recovery and reconstruction in FC.

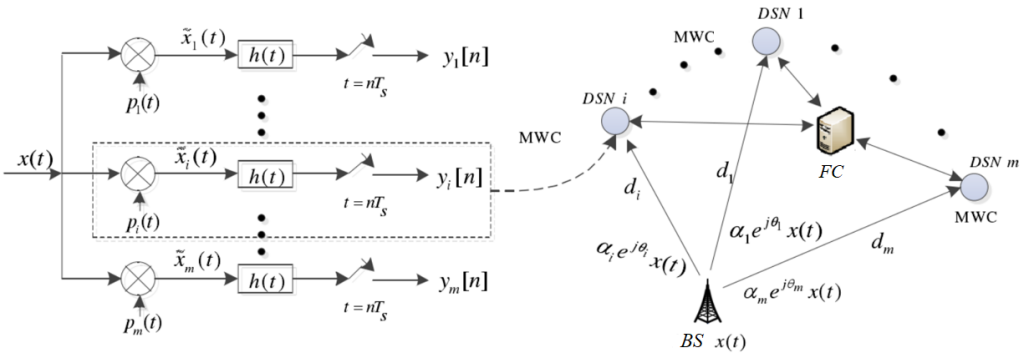

Figure 1. DMWC cooperative spectrum aware network model

In cooperative spectrum sensing network, the distance between transmitting base station and sensing node (DSN_i) is denoted as d_i (I =1,2,3... M). The location distribution of each node is different, so the size of d_i is also different, and the attenuation degree of the signal transmitted to FC is also different.

According to the electromagnetic wave transmission model in the outdoor environment, the transmission attenuation factor can be calculated by the following formula:

$$\alpha_i = \frac{P_a}{P_t} = \frac{G\lambda^2}{(4\pi)^2 d_i^2 F} \tag{1}$$

Where P_a is the received signal power, P_t is the original signal power, G, λ, F are the system gain, signal wavelength and system loss factor respectively. The smaller the α_i is, the more energy the signal loses. DMWC can be used to estimate α_i in a real outdoor environment with few obstacles.

2.1.2. DMWC frequency domain analysis

In DMWC sensing network, the distance between each node and the base station is different, so the attenuation coefficient in the transmission process of each node is also different. Assuming that the signal transmission attenuation coefficient is $\alpha_i \in (0,1), 1 \le i \le m$, then the signal $x_i(t)$ received by the ith sensing node can be expressed as

$$x_i(t) = \alpha_i x(t) \quad (i = 1,2,3 \dots m) \tag{2}$$

In this process, the spectrum information of the original signal is moved to the base band position. Then, the signal spectrum is truncated by a low-pass filter, and finally, the filtered signal is sampled by an ADC sampler. At this time, the low frequency signal already includes the information of the whole frequency band, so the requirement of sampling rate is greatly reduced. The specific process of DMWC spectrum shifting is shown in Figure 2.

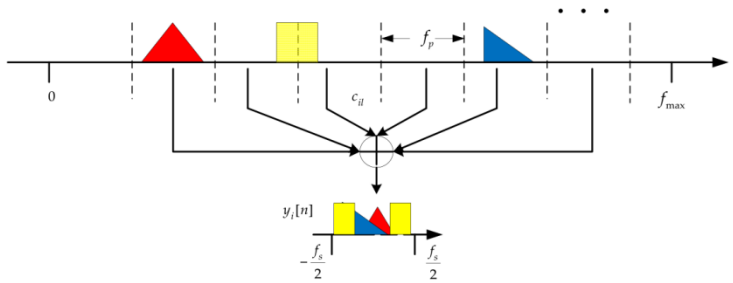

Figure 2. Spectrum moving diagram of DMWC

The output signals of the mixer are $\tilde{x}_i(t) = x_i(t)p_i(t)$, and their Fourier transforms are as follows:

$$\tilde{X}_i(f) = \int_{-\infty}^{+\infty} [x_i(t)p_i(t)]e^{-j2\pi ft}\,dt$$

$$= \int_{-\infty}^{+\infty} \alpha_i x(t)\left(\sum_{l=-\infty}^{\infty} c_{il}e^{j\frac{2\pi}{T_p}lt}\right)e^{-j2\pi ft}dt$$

$$= \sum_{l=-\infty}^{+\infty} \alpha_i c_{il}\int_{-\infty}^{+\infty} x(t)e^{j2\pi\left(f-\frac{1}{T_p}\right)t}$$

$$= \sum_{l=-\infty}^{+\infty} \alpha_i c_{il}X(f - lf_p) \tag{3}$$

The original signal spectrum is evenly cut at f_p intervals, and the spectrum block is moved to baseband superposition. After low-pass filtering and low-speed uniform sampling, the output sampling sequence is

$$Y_i\left(e^{j2\pi fT_s}\right) = \sum_{n=-\infty}^{\infty} y_i\,[n]e^{-j2\pi fnT_s}$$

$$= \sum_{l=-L_0}^{+L_0} \alpha_i\, c_{il}X(f - lf), f \in \left[\frac{-f_s}{2}, \frac{f_s}{2}\right] \tag{4}$$

Where, $L_0 = \left[\frac{f_{Nyquist}+f_s}{2f_p}\right] - 1$. $z(f)$ is used to represent the superposition result of spectrum $X(f)$, which is converted into the matrix form under CS model, and the equivalent formula is obtained as follows

$$y(f) = Az(f), f \in \left[\frac{-f_s}{2}, \frac{f_s}{2}\right] \tag{5}$$

Among them, the measurement matrix A satisfies RIP property, and the support set of the signal is obtained by solving the optimization problem through reconstruction algorithm. The index osition of the support set is the position of the non-zero subband of the spectrum slice.

2.2. SwSAMP blind spectrum reconstruction algorithm

In DMWC sensing network, OMP algorithm is widely used, but this algorithm requires sparsity and maximum subbandwidth of source signal, and is sensitive to signal transmission attenuation. SAMP algorithm can realize spectrum reconstruction under the premise of unknown sparsity, but it is faced with the problems of low reconstruction accuracy and slow convergence. Therefore, this paper proposes an improved SAMP (SwSAMP) algorithm, which

introduces the weak selection strategy and increases the threshold setting during atomic selection to improve the accuracy of the support set selection. Meanwhile, the iterative process adopts the combination of long steps and small steps to approach signal sparsity more quickly and effectively.

Due to the existence of attenuation in DMWC sensing network, the correlation between the column vector of measurement matrix and the sampling matrix will be changed, and the value of inner product calculation result will be affected. So in SwSAMP algorithm, introduced the weak selection strategy, in choosing atomic time increased the threshold set, each choice is not only a perception matrix and residual error matrix of inner product L a maximum value, and expand the inner product of L a maximum value is very close to the maximum of some atoms, pick up and set to enhance the accuracy of the selected support set, selection of threshold values are defined as follows:

$$th = \eta * max(p_i) \tag{6}$$

Where, p_i is the maximum correlation between each column vector of the perception matrix and the sampling matrix.

In the improved SAMP(SwSAMP) algorithm, the method of variable step size is adopted to approximate the sparsity. At the initial stage, the fast approximation with large step length is selected. When the remaining energy difference meets the preset condition, the small step stage is entered and gradually approaches the signal sparsity.

The SwSAMP algorithm flow is shown in Table 1.

Table 1. SwSAMP algorithm steps

Input: Sample sequence y,Perception matrix $A = \Phi\Psi$,Stride S,"weak selection" coefficient η
Step1:Calculate formula $p_k = \sum_{i=1}^{m} r_{A_k R_i}$, get the correlation coefficient matrix PbetweenAandR, k represents the kth column of A
Step2: Calculate the threshold valuethaccording to the formula $th = \eta * \max(\lvert p_i \rvert)$;
Step3: Select the atoms that meet the weak correlation according to the "weak selection" criterion$\Lambda_t = \{i : \lvert p_i \rvert > th\}$, and the sequence numbersjofA corresponding to these atoms form the set S_k
Step4: Update the selected serial number, let $C_k = F_{t-1} \cup \{S_k\}$,$A_t = \{a_j\}, j \in C_k$
Step5:Find the least squares solution of $y = A_t\theta_t$ according to the formula $\hat{\theta}_t = \arg\min_{\theta_t} \lVert y - A_t\theta_t \rVert = (A_t^T A_t)^{-1} A_t^T y$
Step6: TheL item with the largest absolute value selected from$\hat{\theta}_t$ is marked as $\hat{\theta}_{tL}$, the L column of the corresponding A_t is marked as A_{tL}, and the corresponding column number of A is marked as Λ_{tL},$F = \Lambda_{tL}$
Step7: Update residual $r_{new} = y - A_{tL}\left(A_{tL}^T A_{tL}\right)^{-1} A_{tL}^T y$;
Step8: (1)If $r_{new} = 0$, stop the iteration and go to step 9; (2)If $\lVert r_{new} \rVert_2 \geq \lVert r_{t-1} \rVert_2$, update the step size$L = L + S$ and return to step 1; (3)If (1) (2)are not met,$F = \Lambda_{tL}$,$r_t = r_{new}$,$t = t + 1$,If $t \leq M$,go to step 9, otherwise return to step 1 to continue the iteration.
Output sparsity estimate $\hat{\theta}_{tL}$ and final support set F.

3. Simulation experiment and conclusion

The signal of the simulation experiment is broadband sparse signal $x(t)$, and the frequency band number $N = 4$ is set. The time domain model of $x(t)$ is as follows

$$x(t) = \sum_{i=1}^{\frac{N}{2}} \sqrt{E_i B}\, sin\, c\,(B(t-\tau_i))\, cos(\,2\pi f_i(t-\tau_i)) \tag{7}$$

Where, the coefficient of energy $E_i \in \{1,2\}$, bandwidth $B_i \in \{50,50\}MHz$ MHz, time delay $\tau_i \in \{0.7,0.4\}\mu s$, $f_{nyq} = 10GHz$, $f_i \in \left[-\frac{f_{nyq}}{2}, \frac{f_{nyq}}{2}\right]$, random sequence length is $M = 195$, channel number $m = 40$, Sampling frequency $f_s = f_p = \frac{f_{nyq}}{L} = 51.28MHz$. In order to reflect the anti-build performance of the algorithm, gaussian white noise $n(t)$ is added to the original signal, that is, the simulated signal is $x(t) + n(t)$, $SNR = 10log(\|x\|^2/\|w\|^2)$. Each simulation ran 500 Monte Carlo cycles.

3.1. Relationship between transmission attenuation and recovery success rate of support set

In order to verify the tolerance of SwSAMP algorithm to transmission attenuation, SNR is set as 20dB, attenuation coefficient $\alpha_i \in (0,1)$, and the success rate of support set reconstruction under SwSAMP algorithm, SAMP algorithm and OMP algorithm is compared when 0.1 is taken as step. As can be seen from Figure 3, the smaller the attenuation coefficient is, the more serious the signal attenuation is. When $\alpha_i \geq 0.3$, the recovery success rate of the support set is more than 90%. Compared with SAMP and OMP algorithms, the same recovery rate is guaranteed, and the attenuation coefficient increases to at least 0.6. Therefore, it can be shown that the SwSAMP algorithm proposed in this paper can improve the tolerance of DMWC sensing network to signal attenuation.

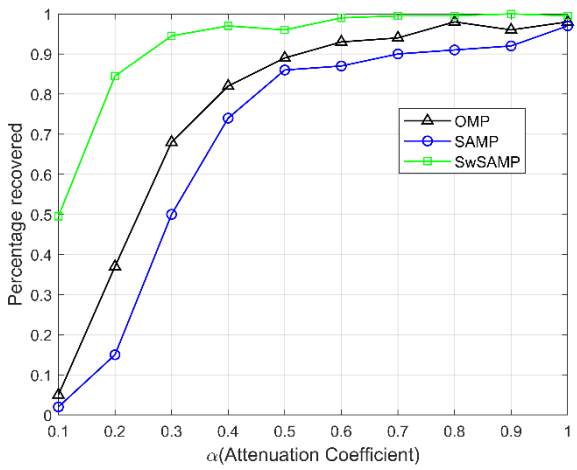

Figure 3. Relationship between transmission attenuation and recovery success rate of support set

3.2. Relationship between the number of channels and the recovery success rate of the support set

In Figure 4, the number of channels increases by 1 step within the interval [10,40]. It can be seen from the figure that when m=21, the recovery rate of SwSAMP algorithm is 90%, which is significantly higher than the other two algorithms. When m $\geq$ 22 , the recovery rate of SwSAMP algorithm is basically above 90%, while OMP and SAMP algorithms need to continue to increase the number of sensing nodes to ensure correct signal recovery. Therefore, the algorithm

proposed in this paper can greatly reduce the number of sensing nodes required and reduce the hardware overhead of DMWC system.

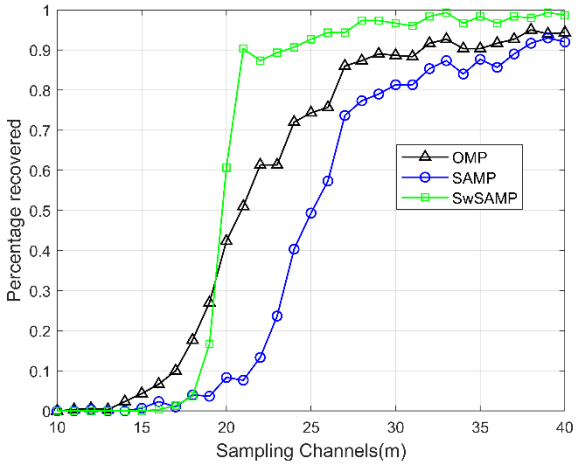

Figure 4. The relationship between the number of channels and the success rate of support set recovery

3.3. Relationship between the number of band and the recovery success rate of the support set

In Figure 5.shows the support set reconstruction accuracy when the number of signal bands increases by 2 steps within the interval [2,18]. With the increase of N, the recovery success rate will decrease due to the limitation of channel number. When $N \geq 12$, the performance of SwSAMP algorithm also decreases sharply and almost loses the recovery ability. This is mainly because in this case the signal will no longer be regarded as sparse. But in general, the recovery rate of SwSAMP algorithm is higher than that of SAMP and OMP algorithm in the whole frequency band range.

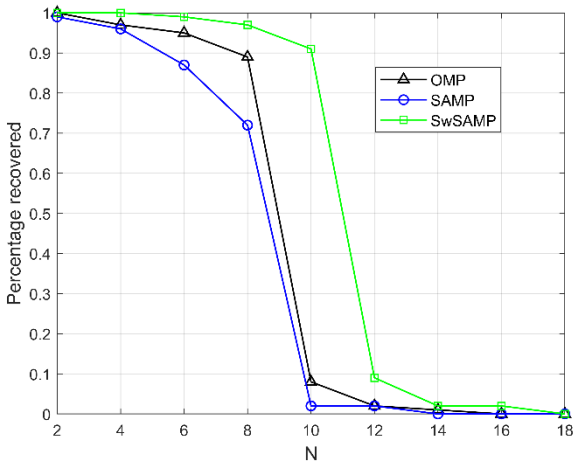

Figure 5. The relationship between frequency band number and recovery success rate of support set

4. Conclusion

Aiming at the problem that it is difficult to accurately obtain the frequency band number of signals in practical applications, this paper proposes a blind spectrum reconstruction algorithm (SwSAMP) for DMWC sensing network. It can be concluded from the comparative experiments that the SwSAMP algorithm can not only improve the tolerance of DMWC system to attenuation, but also reduce the number of sensing nodes and improve the sparsity of signals under the

condition of ensuring accurate signal reconstruction, thus theoretically reducing the pressure of DMWC hardware in real electromagnetic environment.

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