Research Article

A Simplified Multiband Sampling and Detection Method Based on MWC Structure for Mm Wave Communications in 5G Wireless Networks

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The millimeter wave (mm wave) communications have been proposed to be an important part of the 5G mobile communication networks, and it will bring more difficulties to signal processing, especially signal sampling, and also cause more pressures on hardware devices. In this paper, we present a simplified sampling and detection method based on MWC structure by using the idea of blind source separation for mm wave communications, which can avoid the challenges of signal sampling brought by high frequencies and wide bandwidth for mm wave systems. This proposed method takes full advantage of the beneficial spectrum aliasing to achieve signal sampling at sub-Nyquist rate. Compared with the traditional MWC system, it provides the exact quantity of sampling channels which is far lower than that of MWC. In the reconstruction stage, the proposed method simplifies the computational complexity by exploiting simple linear operations instead of CS recovery algorithms and provides more stable performance of signal recovery. Moreover, MWC structure has the ability to apply to different bands used in mm wave communications by mixed processing, which is similar to spread spectrum technology.

1. Introduction

In wireless communication, the most common means of signal transmission is to modulate the information signals by the high carrier frequency. Taking current situations of lower frequency spectrum into consideration, which are crowded and about to run out at present, the next generation (5G) mobile network not only exploits the reintegration of the original spectrum but also is towards higher frequencies.

The explosive growth of consumer demand leads to higher transmission rate. The contradiction between capacity demand and spectrum shortage has become increasingly prominent. Bandwidth is considered a bottleneck, which restricts the development of 5G mobile communication networks. And the mm wave communications have been proposed to be an important part of 5G mobile networks [1, 2]. The application of mm wave communications will be bound to bring new challenges. Many countries, such as the United States, Japan, and South Korea, have opened up to the 60 GHz millimeter wave frequency band, because there is

an abundance of available spectrum surrounding 60 GHz to support the high-rate wireless communications [3]. However, there exists the severe oxygen absorption in the 60 GHz band. Fortunately, the frequency bands 71–76 GHz and 81–86 GHz, collectively called the E-band, have been released to provide broadband wireless services with low atmospheric attenuation, but E-band propagation loss is severe [4]. To further increase the data rate and transmission distance, the MIMO technique has been widely adopted to bring high transceiver complexity in such large MIMO systems with a large number of antennas. To reduce the complexity of systems, more advanced antenna arrays have been used, such as uniform circular array, which is studied in [5, 6]. On the other hand, researches on MIMO channel over such bands have become more important [7]. And input and output signals of MIMO channel are considered multiband signal model, which describes that a group of several transmission signals are modulated by high carrier frequencies. From the perspective of frequency domain, this kind of signal only has values within several continuous intervals spreading over a

wide frequency spectrum. Such feature is called the sparse structure, which is used to achieve signal sampling at low rate.

As sampling technology expands, nonuniform periodic sampling was considered, namely, coset sampling [8]. For one-dimensional multiband signals with arbitrary frequency support, it could be sampled without loss arbitrarily close to the theoretically minimum rate in the scenario of nonuniform sampling [9]. In [10], a universal sampling pattern and corresponding reconstruction algorithms were developed. And it could guarantee well-conditioned reconstruction of all multiband signals with a given spectrum occupancy bound without prior knowledge of spectral support. Exploiting the conditions of exact reconstruction, an explicit reconstruction formula has been derived [11]. In [12], there was an iterative algorithm for finding the minimum sampling frequency for multiband signals, even when the ordering of replicas was constrained. Another method of reconstructing multiband signals with arbitrary spectrum support has been presented, allowing the use of low sampling rates close to the Landau rate, the theoretically lowest sampling rate that still permits perfect reconstruction of the sampled signal [13].

With the rapid development of Compressed Sensing (CS) theory, it brought new ideas for processing of multiband signal [14, 15], in order to solve the problems of large bandwidth and big data. A novel Analog-to-Information Converter (AIC) architecture has been developed [16], in which the multiband signal would pass a wideband pseudorandom demodulator, then integrated, and sampled at a low rate. With the sampling below the Nyquist rate, it presents promising reconstruction results. In [17], by the solution of one-finite-dimensional problem, a method for joint recovery of the entire set of sparse vectors has been developed and it takes the continuous problem into a finite-dimensional one. In [18], it has proved that the recovery of an arbitrary number of jointly sparse vectors was equivalent to the recovery of a finite set of sparse vectors. In [19], under mild conditions on the sparsity and measurement matrix, the analysis of average-case performance of $l_{1,2}$ recovery of multichannel signals has been given. The spectral support without any information in the reconstruction stage, a perfect reconstruction scheme from point-wise sub-Nyquist rate samples for multiband signals, has been proposed, which could ensure the perfect reconstruction for multiband signals sampled at the minimal rate [20, 21]. At present, the widely used method of multiband signals with wide band is a system called the Modulated Wideband Converter (MWC), which was proposed in [22]. This system could be used to process wideband sparse multiband signals with no prior information on the transmitter carrier positions. The multiband signal was firstly multiplied by a bank of periodic waveforms. The product was then low-pass filtered and sampled uniformly at a low rate, which could reduce the sampling rate significantly. To realize the proposed MWC, the circuit has been presented, which could sample multiband signals according to their actual bandwidth occupation [23, 24]. A technique to tackle conventional analog mismatch errors in direct conversion receivers has been presented, including the mathematical derivation about robustness under similar error environments [25]. In [26], it has developed performance limits of

sparse signals support recovery when Multiple Measurement Vectors (MMV) were available and the proposed methodology also had the potential to address other theoretical and practical issues associated with sparse signal recovery. In order to solve the problem of joint sparse recovery, five greedy algorithms designed for the Single Measurement Vector (SMV) sparse approximation problem have been extended to the MMV problem [27]. Another novel approach to obtaining the solution to a sequence of SMV problems with a joint support has been presented, which could be adaptive in that it was solved as a sequence of weighted SMV problems rather than collecting the measurement vectors and solving the MMV problem [28].

In order to achieve higher transmission rate, the transmission signal will become the broadband signal. So it will bring more pressure to sampling and storage devices, especially for hardware implementation. As a result, more and more attention is focused on the broadband multiband signal sampled at sub-Nyquist rate. Due to the capability of processing the broadband signal, MWC system seems to be the best choice to process multiband signals with sparse spectrum structure, which can not only be used in the scenario of arbitrary frequency support but also achieve the signal reconstruction without any prior information about the spectral support [29]. Furthermore, MWC technology has been widely used in the field of cognitive radio to achieve wideband spectrum sensing [30, 31]. However, MWC runs by adopting the idea of CS, which contains many restrictions, in which the number of observation times is the most important problem. The number of sampling channels is equivalent to the MWC system, which makes effects on the reconstruction performance. Present researches cannot offer an explicit solution, so it leads to the unsatisfactory and unstable performance of signal reconstruction followed by the present principles, and it also brings enormous difficulties to the realization of hardware.

In this paper, we propose a simplified multiband sampling and detection method based on the traditional MWC structure which can avoid the challenges of signal sampling brought by high frequencies and wide bandwidth for mm wave systems. For the scenario of signals with arbitrary frequency support, only MWC has the ability to reconstruct them without any prior knowledge, but its performance is not ideal. Based on MWC structure, this proposed method takes full advantage of the beneficial spectrum aliasing to achieve signal sampling at sub-Nyquist rate. Compared with the traditional MWC system, it provides the exact quantity of sampling channels which is far lower than that of MWC. In the reconstruction stage, the proposed method simplifies the computational complexity by exploiting simple linear operations instead of CS recovery algorithms and provides more stable performance of signal recovery. Moreover, MWC structure has the ability to apply to different bands used in mm wave communications by mixed processing, which is similar to spread spectrum technology.

The remainder of this paper is organized as follows. Section 2 describes the principle of MWC system and some problems. We present a method of mm wave communications

FIGURE 1: The sampling part of MWC structure.

based on MWC structure in Section 3. Simulation results discussed in Sections 4 and 5 conclude the paper.

2. MWC System and Problem Statements

MWC system aims at efficient hardware implementation and low computational loads on the digital processing. In the reconstruction stage, the equation of CS theory ingeniously is combined to obtain the frequency support, which is the key to reduce the complexity of signal recovery and allow the low-rate processing [22]. The principles of MWC are as follows.

2.1. MWC Structure and Principle. The inspiration of MWC structure comes from the thought of AIC architecture and conventional parallel data processing methods. For MWC structure, an analog mixing front-end achieves the spectrum alignment, whose goal is to make a spectrum portion from each band appear in baseband. It is the most important part to realize the low-rate sampling.

An analog mixing front-end consists of several channels and uses the mixing function $p_i(t)$ to obtain different mixing of an analog multiband signal $x(t)$, which includes several transmission signals modulated by high carrier frequencies. And the mixing function $p_i(t)$ is similar to pseudorandom code in spread-spectrum techniques, which is chosen as a piecewise constant function that alternates between two levels.

Considering the limitation of CS theory, the number m of processing channels should reach a certain amount, to recover such a sparse multiband signal. The sampling part of MWC structure is depicted in Figure 1. After mixing, the mixtures are truncated by the same low-pass filters with cutoff $1/(2T_s)$. Then, the filtered signal is sampled at low rate T_s relative to the carrier frequencies of the input signal by using common sampling theory.

According to [22], we know that the input of LPF $h(t)$ is a linear combination of f_p -shifted copies of $X(f)$, where f_p is the frequency of the mixing function $p_i(t)$ and $X(f)$ stands for the Fourier transform of the multiband signal $x(t)$. After low-pass filtering, only the part in baseband is retained, which includes information from each band. And then, the filtered signal is sampled uniformly at rate T_s which is matched to

FIGURE 2: Continuous to finite block.

the cutoff frequencies of LPF. Finally, the channel output $y_i[n]$ can be obtained and the total samples $\mathbf{y}[n]$ are used to recover the signal. The relation between the sample sequences $y_i[n]$ and the input signal $x(t)$ is expressed as in frequency domain:

$$\begin{aligned} Y_i(e^{j2\pi f T_s}) &= \sum_{n=-\infty}^{\infty} y_i[n] e^{-j2\pi f n T_s} \\ &= \sum_{l=-\infty}^{\infty} c_{il} X(f - l f_p), \end{aligned} \quad (1)$$

where c_{il} represents the Fourier coefficients of the mixing function $p_i(t)$.

Rewrite (1) in matrix form as

$$\mathbf{y}(f) = \mathbf{A} \mathbf{z}(f), \quad (2)$$

where $\mathbf{y}(f)$ is made up of the element $y_i(f)$, the Discrete-Time Fourier Transform (DTFT) of i th sequence $y_i[n]$. Matrix $\mathbf{A}$ contains the coefficients c_{il} and $\mathbf{z}(f)$ consists of f_p -shifted copies of $X(f)$, which has sparse structure.

Considering (2), it is similar to the typical problem in CS theory. So, in the reconstruction stage, CS is integrated to acquire the carrier frequency support. Solving (2) directly is regarded as the IMV problem, which is so difficult. In this system, another method has been proposed in [15, 21]. This method has a two-step flow which recovers the frequency support set from a finite-dimensional system at first and then recovers the signal. For the first step, the algorithm constructs a finite frame $\mathbf{V}$ from the sample sequence, which can be obtained by computing [15]

$$\mathbf{Q} = \int_{f \in F_s} \mathbf{y}(f) \mathbf{y}^H(f) df = \sum_{n=-\infty}^{+\infty} \mathbf{y}[n] \mathbf{y}^T[n]. \quad (3)$$

And then, any matrix $\mathbf{V}$ comes from $\mathbf{Q} = \mathbf{V} \mathbf{V}^H$. F_s denotes the frequency range $F_s = [-f_s/2, f_s/2]$ with $f_s = 1/T_s$.

In the second step, it finds the unique solution $\bar{\mathbf{U}}$ to the MMV system $\mathbf{V} = \mathbf{A} \mathbf{U}$ that has the fewest nonzero rows and the frequency support of $\bar{\mathbf{U}}$ equals that of the multiband signal $x(t)$. The whole operations are gathered in a block named continuous to finite (CTF), depicted in Figure 2.

In this part, the recovery algorithm under CS theory is exploited to obtain the spectrum support, taking full advantage of spectral sparsity. It is also the key of the whole system. However, CS recovery algorithms have their own computation complexity, mostly from iterative procedure. After finding band position, the multiband signal is recovered by the position index information.

2.2. Problem Statement. As mentioned above, the biggest feature of MWC system is to apply CS theory to construct multiband signals with sparse structure at low sampling rate well below the Nyquist rate.

CS theory is to solve the problem based on the probability. In order to achieve a high probability of reconstructing signal, certain conditions must be met in the process of sampling; in other words, the requirements for sampling times of signal should be up to a certain amount. Though sampling rate under CS theory can be far below the Nyquist rate, there still exists a theoretical lower bound value, which is not being applied directly because of a big difference to the practical application. In fact, the quantity used in practice is larger than that, sometimes far larger than that, which is still less than the requirements of Nyquist sampling theorem.

In MWC system, combined with the typical equation under CS theory, all the mixing functions make up the measurement matrix and the number of sampling channels is row number of matrices, in other words, the times of observation. In order to recover the sparse signal in the reconstruction stage, the amount of sampling channels should be more enough. In [22], the relationship between the number of bands N and the quantity of sampling channels m in theory is given; namely, $m \geq N$ for nonblind reconstruction or $m \geq 2N$ for blind reconstruction. However, the simulation results, which is described later in Section 4.1, show that just meeting the relationship is far from enough.

Because the requirements of observation times are not clear and taking into account the fact that there are the great differences between the theory and the actual situation, when facing the unknown number of bands N , the clear basis of the sampling channel selection in practical application is not given. Just taking successful recovery as standard, the reference value of the sampling channel amount is offered from the perspective of experience. Even so, facing the unknown signal in application, a certain error of reference value still exists. The number of bands N has great effects on the selection of sampling channels. In order to ensure the signal recovery, it is easy to think of the effective methods to increase the number of sampling channels. However, such increasing numbers will bring more difficulties to hardware implementations, which means that more components would be needed, adding the costs of the system, as well as extra burden on calculation process due to more data.

The most striking feature of MWC system is to handle the multiband signal with sparse structure at a low rate, far below the Nyquist rate. The total sampling rate of MWC is the product of the channel number and the actual sampling rate of each channel. Therefore, increasing the number of sampling channels is undoubtedly to raise the total sampling rate, which reduces the advantages of MWS system greatly. Although a method to reduce the actual physical channel by using collapse factor with the costs of improving the sampling rate is given [22], under the existing technology, such problem is not solved radically. On the other hand, even if the sampling channel is enough, it leads to the instability recovery performance, which is even not satisfied because of the unstable property of CS recovery algorithm, and is shown later in Section 4.1.

The expectation is to fundamentally solve the problems of the uncertain quantity of sampling channels and the unstable performance of recovery; besides, new ideas and methods should be taken into account. In this paper, based on comprehensive considerations of the above issues and getting inspiration from MWC structure, as well as its ability to deal with the signal which has arbitrary frequency support, a simplified multiband sampling and detection method based on MWC structure for mm wave communications is presented; main thought is to exploit the beneficial spectrum aliasing, as shown in Section 4.2. Starting from the characteristics of the aliasing spectrum, the frequency supports about each carrier frequencies are acquired by calculation. Then, each band is separated to obtain the integrated information from the aliasing spectrum, to avoid the uncertainty results brought by CS. More detail about this method is described in Section 3.

3. A Simplified Multiband Method Bands Based on MWC Structure for Mm Wave Communications

Considering the ability to process the multiband signal with arbitrary frequency support, MWC technology can be used for signals in mm wave communications, which may be common in 5G mobile networks. However, MWC system is not applied directly because of the problems of the uncertain conditions of sampling channel quantity and unstable reconstruction results.

A simplified multiband sampling and detection method is proposed in this paper, taking MWC structure into account and exploiting the beneficial spectrum aliasing. After mixing and low-pass filtering, the results present the superposition of shifted copies from each band modulated by the Fourier coefficients of the mixing functions, depicted in Figure 3. However, these coefficients that belong to any channel are different from each other based on the frequency support, and it is also different for the same band in different sampling channel because of the different mixing functions. There exists a fact that, for the same band in different channels, the effects brought by the spectrum support are the same. These are also the basis of this method.

3.1. Calculation Process. To achieve the spectrum aliasing, this method also exploits the spread-spectrum techniques to multiple the inputs by T_p -periodic waveforms $p_i(t)$. Based on MWC structure, which is shown in Figure 2, after mixing, the mixtures can be expressed as $\tilde{x}_i(t) = x(t)p_i(t)$.

Considering any i th channel, the Fourier transform of the mixing functions is as follows:

$$c_{il} = \frac{1}{T_p} \int_0^{T_p} p_i(t) e^{-j(2\pi/T_p)lt} dt, \quad (4)$$

where

$$p_i(t) = \sum_{l=-\infty}^{\infty} c_{il} e^{j(2\pi/T_p)lt}. \quad (5)$$

FIGURE 3: Results of mixing and low-pass filtering.

So the mixture has a Fourier expansion

$$\begin{aligned}
 \tilde{X}_i(f) &= \int_{-\infty}^{\infty} \tilde{x}_i(t) e^{-j2\pi ft} dt \\
 &= \int_{-\infty}^{\infty} x(t) \left(\sum_{l=-\infty}^{\infty} c_{il} e^{j(2\pi/T_p)lt} \right) e^{-j2\pi ft} dt \\
 &= \sum_{l=-\infty}^{\infty} c_{il} \int_{-\infty}^{\infty} x(t) e^{-j2\pi(f-l/T_p)t} dt \\
 &= \sum_{l=-\infty}^{\infty} c_{il} X(f - l f_p).
 \end{aligned} \tag{6}$$

It represents a linear combination of f_p -shifted copies of $X(f)$. After low-pass filtering, only the part in baseband is retained, so it includes small copies from each band. Their amplitudes are determined by the mixing functions and the frequency support. Obviously, if the spectrum support can be acquired, it is possible to deduce which copies for each band are retained, which is the key of this method. In order to achieve this purpose, first the spectrum can be divided into frequency intervals and code each interval. According to the number of frequency intervals, the locations of each band can be determined. Later, in Section 3.2, there are some details about parameter selection, especially the relation between frequencies of the mixing functions and the LPF cutoff. Assuming that filtered signal contains only one copy of each band and is guaranteed by the parameter selection, for the multiband signal with N subsignals, the sampled signal of i th channel can be expressed as

$$y_i(f) = \sum_{k=1}^N c_{il_k} X_k(f_k - l_k f_p). \tag{7}$$

Rewrite (7) in matrix form as

$$y_i(f) = [c_{il_1} \ c_{il_2} \ \cdots \ c_{il_N}] \begin{bmatrix} X_1(f_1 - l_1 f_p) \\ X_2(f_2 - l_2 f_p) \\ \vdots \\ X_N(f_N - l_N f_p) \end{bmatrix}, \tag{8}$$

where $y_i(f)$ is the DTFT of the i th sequence $y_i[n]$. f_k represents the frequency support of each band and $X_k(f)$ is the spectrum of each signal band. l_k stands for the label number of shifted copies of $X_k(f)$. So $X_k(f - l_k f_p)$ is l_k th f_p -shifted copies of each band. The Fourier coefficients c_{il_k} are determined by the mixing functions $p_i(t)$ in (5) and l_k .

And l_k is defined as follows:

$$l_k = \frac{f_k}{f_p}. \tag{9}$$

For the different sampling channels, the parameters l_k of each band are the same. Suppose l_k is a constant and derive the expression of $X_k(f - l_k f_p)$. For all m sampling channels, get the equation

$$\begin{bmatrix} y_1(f) \\ y_2(f) \\ \vdots \\ y_m(f) \end{bmatrix} = \begin{bmatrix} c_{1l_1} & c_{1l_2} & \cdots & c_{1l_N} \\ c_{2l_1} & c_{2l_2} & \cdots & c_{2l_N} \\ \vdots & \vdots & \ddots & \vdots \\ c_{ml_1} & c_{ml_2} & \cdots & c_{ml_N} \end{bmatrix} \begin{bmatrix} X_1(f_1 - l_1 f_p) \\ X_2(f_2 - l_2 f_p) \\ \vdots \\ X_N(f_N - l_N f_p) \end{bmatrix} \tag{10}$$

or

$$\mathbf{Y}(f) = \mathbf{A}\mathbf{X}^*. \tag{11}$$

To solve the equations with N unknown numbers, N equations are required; namely, $m = N$. With reference to the method of solving linear equations, the expression of $X_k(f)$ is

$$(\mathbf{A} | \mathbf{Y}) = \left(\begin{array}{cccc|c} c_{1l_1} & c_{1l_2} & \cdots & c_{1l_m} & y_1(f) \\ c_{2l_1} & c_{2l_2} & \cdots & c_{2l_m} & y_2(f) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ c_{ml_1} & c_{ml_2} & \cdots & c_{ml_m} & y_m(f) \end{array} \right). \tag{12}$$

By transforming the augmented matrix, we can obtain the following form:

$$(\mathbf{A} | \mathbf{Y}) \rightarrow \left(\begin{array}{cccc|c} 1 & 0 & \cdots & 0 & d_1(f) \\ 0 & 1 & \cdots & 0 & d_2(f) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & d_m(f) \end{array} \right), \tag{13}$$

where $d_i(f)$ is the linear combination of $y_i(f)$ and equal to $X_k(f_k - l_k f_p)$. Then, the expression $X_k(f_k - l_k f_p)$ is obtained, containing other N unknown numbers of l_k , which demands other N equations.

To acquire the other N equations, we need to carry out the above operation again and connect the two corresponding equations with the bridge of the expression $X_k(f_k - l_k f_p)$. It means that completing the signal recovery needs totally $2N$ equations.

As we know, in MWC system a theoretical conclusion, that is, $m \geq N$ for nonblind reconstruction or $m \geq 2N$ for blind reconstruction, is given. The proposed method has an advantage that it can provide the explicit quantity of sampling channels and solve the reconstruction stability problem. As discussed above, completing the signal recovery needs totally $2N$ equations, while N equations are demanded to obtain the expression $X_k(f_k - l_k f_p)$ and another N equations are needed to get the frequency support l_k . According to the conditions of sampling channels quantity, the proposed method has lower sampling rate than MWC system and can reduce the hardware implementation complexity with few channels.

To simplify the analysis, we consider that the multiband signal has two subsignals $N = 2$.

For the first two channels, we can get the equations

$$\begin{bmatrix} y_1(f) \\ y_2(f) \end{bmatrix} = \begin{bmatrix} c_{1l_1} & c_{1l_2} \\ c_{2l_1} & c_{2l_2} \end{bmatrix} \begin{bmatrix} X_1(f_1 - l_1 f_p) \\ X_2(f_2 - l_2 f_p) \end{bmatrix}. \quad (14)$$

Solving (14),

$$X_1(f_1 - l_1 f_p) = \frac{c_{2l_2} y_1(f) - c_{1l_2} y_2(f)}{c_{1l_1} c_{2l_2} - c_{1l_2} c_{2l_1}}, \quad (15a)$$

$$X_2(f_2 - l_2 f_p) = \frac{c_{2l_1} y_1(f) - c_{1l_1} y_2(f)}{c_{1l_2} c_{2l_1} - c_{1l_1} c_{2l_2}}. \quad (15b)$$

And the same procedure may be easily adapted to obtain another two channels:

$$X_1(f_1 - l_1 f_p) = \frac{c_{4l_2} y_3(f) - c_{3l_2} y_4(f)}{c_{3l_1} c_{4l_2} - c_{3l_2} c_{4l_1}}, \quad (16a)$$

$$X_2(f_2 - l_2 f_p) = \frac{c_{4l_1} y_3(f) - c_{3l_1} y_4(f)}{c_{3l_2} c_{4l_1} - c_{3l_1} c_{4l_2}}. \quad (16b)$$

Simultaneous equations (15a) with (16a) and (15b) with (16b) get the equations

$$\begin{aligned} \frac{c_{2l_2} y_1(f) - c_{1l_2} y_2(f)}{c_{1l_1} c_{2l_2} - c_{1l_2} c_{2l_1}} &= \frac{c_{4l_2} y_3(f) - c_{3l_2} y_4(f)}{c_{3l_1} c_{4l_2} - c_{3l_2} c_{4l_1}}, \\ \frac{c_{2l_1} y_1(f) - c_{1l_1} y_2(f)}{c_{1l_2} c_{2l_1} - c_{1l_1} c_{2l_2}} &= \frac{c_{4l_1} y_3(f) - c_{3l_1} y_4(f)}{c_{3l_2} c_{4l_1} - c_{3l_1} c_{4l_2}}. \end{aligned} \quad (17)$$

The solutions of (16a) and (16b) are the spectrum support l_k^* , $k = 1, 2$. Due to the effect of bandwidth, the sequence numbers of frequency intervals where the bands are occupied may be l_k^* and $l_k^* \pm 1$, written as $\text{Bindex} = \{l_k^* - 1, l_k^*, l_k^* + 1\}$. The

goal of this operation is to avoid the effect resulting from the bands that occupies two consecutive intervals due to arbitrary frequency support.

Once Bindex is found, we can get the submatrix $\mathbf{A}_{\text{Bindex}}$, which contains the columns of $\mathbf{A}$ indexed by Bindex. Recover the information of multiband signal $z_l[n]$ as follows:

$$\begin{aligned} \mathbf{z}_{\text{Bindex}}[n] &= \mathbf{A}_{\text{Bindex}}^+ \mathbf{y}[n], \\ z_l[n] &= 0, \quad l \notin \text{Bindex}, \end{aligned} \quad (18)$$

where $\mathbf{A}_{\text{Bindex}}^+ = (\mathbf{A}_{\text{Bindex}}^H \mathbf{A}_{\text{Bindex}})^{-1} \mathbf{A}_{\text{Bindex}}^H$ is the pseudoinverse of $\mathbf{A}_{\text{Bindex}}$ and $z_l[n]$ is the inverse-DTFT of $z_l(f)$.

This process is a conventional matrix processing. It means that if we can recover the frequency support successfully, we will get the original signal.

3.2. Parameters Selection and Performance Analysis. The copy of $X_k(f)$ retained after low-pass filtering is the one that locates around zero frequency in baseband, so the number of frequency intervals L should be odd, which is also determined by the frequencies of mixing functions f_p ; in other words, L stands for the number of f_p -shifted copies of each band

$$L = \frac{f_{\max}}{f_p}, \quad (19)$$

where $f_{\max}$ represents the highest frequency of the multiband signal.

This method exploits the beneficial spectrum aliasing from different bands. To avoid the aliasing from the single band, the frequencies of mixing functions f_p should be larger than the maximum bandwidth of all bands; namely, $f_p \geq B$. The output of LPF contains only one copy of each band, matching the shifting effect, so the cutoff of LPF f_s should be equal to f_p . So it is easily seen that only if f_p is chosen as B , the minimum sampling rate can be achieved.

The basis of the selection of main parameters is to offer the beneficial spectrum aliasing and this is the key of the proposed method. The choice of the mixing function frequencies can make sure that after low-pass filtering, there are only small copies in baseband retained to avoid aliasing themselves. The method exploits the beneficial spectrum aliasing and samples the low-pass filtered signal at a low rate to obtain the information about each band of the multiband signal. Combined with signal superposition principle, the spectrum support about each carrier frequency is acquired by calculating the finite samples through a certain quantity of sampling channels. And the amount of channels is equal to twice of the number of subsignals. After that, each band is separated from the spectrum aliasing and the multiband signal recovery is completed. The proposed method replaces the partial processing steps in MWC system and eliminates the uncertainty factors. For the frequency support recovery, this method exploits simple linear operations instead of CS recovery algorithm, which can improve the performance of signal recovery. This is also the greatest advantage of the method. Meanwhile, MWC system has the unstable and unsatisfactory reconstruction performance. More details of the simulation results will be presented in next part.

4. Simulation Results

We now demonstrate several performance aspects of MWC system and our approach by using the simulation results. In this paper, taking multiband signals in mm wave communications as the research object, a simplified multiband sampling and detection method based on MWC structure is presented to solve the problem of uncertain quantity of sampling channels in MWC system. The multiband signal model is described as follows:

$$x(t) = \sum_{i=1}^N \sqrt{E_i B_i} \text{sinc}(B_i(t - \tau_i)) \cos(2\pi f_i(t - \tau_i)). \quad (20)$$

There are N pairs of bands (or N subsignals), because two symmetrical couples stand for one subsignal and $2N$ is the number of the total bands. B_i stands for the width of each band; E_i represents the energy coefficients and τ_i is the time offsets. For each subsignal, the carrier frequencies f_i are chosen uniformly at random in the interested range.

The proposed method starts with the situation of non-clear conditions for the sampling channel quantity and the imperfect performance of signal reconstruction, as shown in the first part. Then, the method exploits the MWC structure, especially the beneficial aliasing spectrum, depicted in the next part. Finally, the advantage of the proposed method will be demonstrated.

4.1. Reconstruction Performance of MWC System. In the reconstruction stage of MWC system, CS theory is integrated into the process. The mixing functions play the role of the measurement matrix. In order to recover the multiband signal, the quantity of sampling channels should be enough. However, in fact the theoretical value is far from enough. As mentioned above, we know the key of the signal processing is to recover the frequency support, which decides the final results. Thus, let the rate of correct support recovery be the reference object to measure the reconstruction performance.

The carrier frequency f_i is chosen uniformly at random in the range [60 GHz, 70 GHz] and the value B is chosen from 20 MHz to 300 MHz. The number of subsignals N is equal to 1, 2, and 3. Simulation process is repeated 1000 times to show the performance of signal recovery. And the number of sampling channels ranges from 10 to 100. The simulation results are demonstrated in Figures 4, 5, and 6.

In these three figures, it is easily seen that, for the same N , there are different results with different bandwidths. On the whole, the results with $N = 1$ have the best performance; since the number of bands grows, the correct support recovery rate decreases. However, in one figure this rate is not decided by the bandwidth simply; especially for Figures 5 and 6, the smallest bandwidth $B = 20$ MHz has the lowest success rate. The vast majority of success rate is lower than 90%; even for the case of one subsignal, there are also several results below 90%.

On the other hand, when the success rate of support recovery can reach up to 90%, in the case of one subsignal, mostly more than ten channels are needed, and in other two

FIGURE 4: Recovery performance with one subsignal.

cases, even if the number of sampling channels is larger than ten times of N , the simulation results are still unsatisfactory.

Conclusively, the simulation results show that the signal recovery is unstable and mostly unsatisfied, just since CS theory is to solve the problem based on the probability and nonclear condition of sampling channels. Because of the property of instability, it cannot play a guiding role in practical application.

4.2. Result of the Mixing Stage. The method exploits the beneficial spectrum aliasing. After low-pass filtering, only the part in baseband is retained, which includes information from each band. And we sample the low-pass filtered signal at a low rate to obtain the information about every band of the multiband signal. These are also the bases of this method. For simplifying, we consider the case of two subsignals. The carrier frequency f_i is chosen uniformly at random in the range [71 GHz, 76 GHz], and the bandwidth B is 500 MHz. The positive frequency part of signal spectrum is shown in Figure 7. Here, the sampling rate f_s is slightly larger than B .

In Figure 8, there are the sampled signals of the output of LPF from channel 1 and 2. It is easily seen that the only difference among each channel is the magnitude effects caused by the Fourier coefficients of the mixing functions.

FIGURE 5: Recovery performance with two subsignals.

FIGURE 6: Recovery performance with three subsignals.

We can also see that the locations of shifted copies which belong to each band are the same in baseband due to the same frequency support and the same band in different sampling channels are different caused by the different mixing functions. In baseband, several copies from different bands alias together, including all information of bands and it is called the beneficial spectrum aliasing. And this method is put forward just based on these characteristics.

4.3. System Sampling Rate Comparison. As discussed above, MWC system has unstable effects on signal recovery. And the simulation results with $N = 1$ have the best performance; as the number of bands grows, the correct support recovery rate decreases. In order to compare the whole system sampling rate between MWC system and the proposed one, we choose the case of one subsignal. For two methods, the sampling rate of each channel is in both chosen slightly larger than bandwidth B . As shown in Figure 9, we only consider the cases that the correct support recovery rate is more than 90%.

The system sampling rate is the product of the channel quantity and the actual sampling rate of each channel. Since this method provides the exact conditions of sampling channels quantity, which is equal to the minimum limit theoretical value of MWC system, it is possible to handle the

signal with the lower sampling rate than MWC system. It is seen in Figure 9, whose ordinate is the ratio of the sampling rate of MWC to that of the proposed one, that the proposed method has lower sampling rate.

5. Conclusion

In this paper, a simplified multiband sampling and detection method based on MWC structure is proposed for mm wave communications. MWC structure which is multichannel parallel provides the beneficial spectrum aliasing. Starting from it, the low-pass filtered signal is sampled at a low rate to obtain the information about each band of the multiband signal and to acquire the spectrum support by calculating the finite samples using a certain quantity of sampling channels. Then, each copy can be separated from the aliasing spectrum and on this basis to recover the multiband signal. Compared with the traditional MWC technology, the proposed method provides the exact conditions on sampling channels quantity, which is smaller than that of traditional MWC system. And it means that the sampling rate of the whole system is much lower. Moreover, the main idea of the proposed method is to get the spectrum support. Compared with the traditional MWC systems integrated CS theory, the proposed method

FIGURE 7: Spectrum of original multiband signal.

FIGURE 8: The beneficial spectrum aliasing from two channels.

FIGURE 9: System sampling rate comparison.

simplifies the computational complexity in the reconstruction stage by using simple linear operations instead of CS recovery algorithm. And it also can avoid the instability and improve the performance of signal recovery due to the certain condition of sampling channels quantity.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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