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A Wideband Receiver with Adaptive Strong Interference Suppression

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Abstract: In this paper, a wideband receiver with high dynamic range is proposed. At the front end of the proposed receiver, a sensing waveform is used to sense the input signal. And by adjusting the sensing waveform so as to project the interference to zero, the receiver can eliminate the strong interference signal adaptively before sampling. Both the theoretic analysis and simulation show that this method can suppress the interference signal effectively and improve the sampling accuracy of the weak desired signal when the instantaneous dynamic range of the input signal is larger than the dynamic range of the ADC's quantizer. *Copyright © 2013 IFSA.*

Keywords: Dynamic range, Strong interference suppression, Compressive sampling, Effective number of bits.

1. Introduction

Wideband radio frequency (RF) signal acquisition receiver can find more and more applications both in commercial communication systems and military systems. At the same time, it is becoming more and more crowded for the radio spectrum. And the wideband receiver has to face signals that have different power levels within receiving bandwidth instantaneously. So, from technical point of view, there are two important attributes that character the receiver, i.e., instantaneous bandwidth and instantaneous dynamic range [1].

According to Nyquist sampling theorem, the sampling rate must be at least twice the maximum frequency present in the signal (the so-called Nyquist rate). So the instantaneous bandwidth of the receiver is decided by the sampling rate of the analog-to-digital converter (ADC). As to the instantaneous dynamic range, it is mainly decided by ADC's effective number of bits (ENOB). To satisfy both the wide receiving bandwidth and the high instantaneous dynamic range, the ADC should have high sampling rate and enough ENOB as well. However, according to the work of [1, 2], it is predicted that the ENOB of an ADC should degrade at a rate of 1bit per octave of sampling rate, over a broad range of sampling rates. As a result, the design of wideband receiver with high dynamic range is full of challenge. Especially, in some applications, the desired signal is weak while the undesired signal is much stronger than it. Constrained to the performance of ADC, when the power ratio between the strong signal and the weak signal is larger than the instantaneous dynamic range of ADC, it is difficult to get the weak signal. That is because the largest spurs, usually produced by distortion components from strong signals at the front end, could mask weak signals processed by the receiver. And if the hybrid receiving signal is attenuated, the quantized noise ratio will be too low to retrieve the information of the weak signal.

There are three kinds of solutions in traditional RF receiver design:

a) To add caving filter at the front end of the receiver. This is the traditional method to suppress strong interference. However, it can only suppress the interference with fixed frequency and cannot deal with the random strong interference.

b) To modeling the nonlinear characteristic of the receiver [3] and then estimate the nonlinear distortion which will be used to compensate the output of ADC at the digital part of the receiver. However the model will change with different components and the characters of the components will change with the environment too.

c) To eliminate the nonlinear distortion before ADC by a kind of feeding forward system [4]. Two channels are used in this system and one of the two channels is used for distortion cancellation. However, in the system, the delays of the two channels have to be controlled accurately to guarantee the exact distortion cancellation. Unfortunately, the accurate analog delay control is very difficult.

An analog-digital hybrid method for adaptive strong interference suppression is proposed in this paper. The method is based on compressed sensing. By adjusting the sensing waveform at the front end of the receiver according to the structure of the interference which is learned by the digital part of the receiver, the receiver can project the strong interference into zero before sampling.

Compressed sensing (CS) [5] is a new technology for sparse signal sampling that goes against to common wisdom of data acquisition. CS shows that it is possible to capture and represent compressible signals at a rate significantly below the Nyquist rate. By employing linear projections that preserve the structure of the signal, CS can get the compressed signal and then reconstruct it by using an optimization process. The most important part of CS is the analog-to-information (AIC) [6] structure.

The method proposed in this paper modifies the structure of the common AIC. By introducing feedback circuit and adjusting the sensing waveform according to the interference, the new receiver based on the new AIC can suppress the strong interference and enhance the dynamic range as a result. There are five parts in this paper. Part 2 sets up the correlated mathematic model. Part 3 introduces the novel method. Part 4 gives the results of simulations and part 5 draws a conclusion.

2. Mathematic Model and System Structure

A. Mathematic model

Suppose that the hybrid signal of the strong interference and the weak desired signal is $S(t)$, then

$$\begin{aligned} S(t) &= S_I(t) + S_d(t) \\ &= \Psi\vec{x} = \Psi\vec{x}_I + \Psi\vec{x}_d \end{aligned}, \tag{1}$$

where $S_I(t)$ is the interference signal and $S_d(t)$ is the desired signal. $\Psi = [\psi_1(t), \psi_2(t), \ldots \psi_N(t)]$ is the orthogonal basis that is used to express the signal and $\vec{x}_I \in R^N, \vec{x}_d \in R^N$ represent the corresponding coefficient vectors of the interference signal and the desired signal respectively. $\vec{x}$ is the sum of $\vec{x}_I$ and $\vec{x}_d$. Suppose that $S(t)$ is K-sparse (K<N), which means that for basis Ψ, there are only K non-zero coefficients. And $\vec{y} \in R^M$ is the M ($M << N$) observations of $S(t)$, then

$$\vec{y} = \Theta(\vec{x}_I + \vec{x}_d), \tag{2}$$

where $\Theta_{M\times N} = \Phi\Psi$ and $\Phi_{M\times N}$ are chosen from the orthogonal basis Φ, which is used to sensing the object $S(t)$. The coherence between the sensing basis Φ and the representation basis Ψ is

$$\mu(\Phi, \Psi) = \sqrt{n} \max_{1\le k, j\le n} \left| < \varphi_k, \psi_j > \right| \tag{3}$$

From linear algebra, we can get that $\mu(\Phi, \Psi) \in [1, \sqrt{n}]$. CS is mainly concerned with low coherence pairs. The signal reconstruction in CS is to solve (2). Since M << N, this problem appears ill-conditioned.

However, if $S(t)$ is K-sparse, the problem will change to the problem of minimum ℓ_0 – norm reconstruction, i.e.

$$\vec{x}^* = \arg(\min_{\vec{x}} \|\vec{x}\|_{\ell_0}), \text{ such that } \vec{y} = \Theta\vec{x}, \tag{4}$$

where $\|\vec{x}\|_{\ell_0} := \sum_{i=1}^{N} |x_i|^0$.

Unfortunately, solving (4) is both numerically unstable and NP-complete requiring an exhaustive enumeration of all $\binom{N}{K}$ possible locations of the nonzero entries in $\vec{x}$.

Practically, it is pointed out that the minimum ℓ_1 – norm reconstruction can solve the problem with high probability too [5, 7]. And the problem can be expressed as

$$\vec{x}^* = \arg(\min_{\vec{x}} \|\vec{x}\|_{\ell_1}), \text{ such that } \vec{y} = \Theta\vec{x}, \tag{5}$$

where $\|\vec{x}\|_{\ell_1} := \sum_{i=1}^{n} |x_i|$.

It is proved that a necessary and sufficient condition for this simplified problem (5) to be well conditioned is that $M \ge cK\log(N/K)$ (c is a small positive constant) and the matrix Θ satisfies RIP (restricted isometry property) [8].

The definition of RIP is:

For each integer K= 1, 2, . . . , define the isometry constant δ_K of a matrix Θ as the smallest number such that

$$(1-\delta_K)\|\vec{x}\|_{\ell_2}^2 \le \|\Theta\vec{x}\|_{\ell_2}^2 \le (1+\delta_K)\|\vec{x}\|_{\ell_2}^2 \qquad (6)$$

holds for all K-sparse vectors $\vec{x}$.

If δ_K is not too close to 1, then the matrix Θ obeys the RIP of order K. And (6) means that if matrix Θ obeys RIP, then any K columns of Θ are nearly orthogonal to each other [10].

As to the strong signal suppression problem which is proposed to be solved in this paper, we hope that the result of the linear projection of the interference will be zero, i.e.

$$\begin{aligned}\vec{y} &= \Theta\vec{x}_I + \Theta\vec{x}_d \\ &= 0 + \Theta\vec{x}_d\end{aligned} \qquad (7)$$

B. System structure

A new adaptive AIC which can adjust the sensing waveform is shown in Fig. 1.

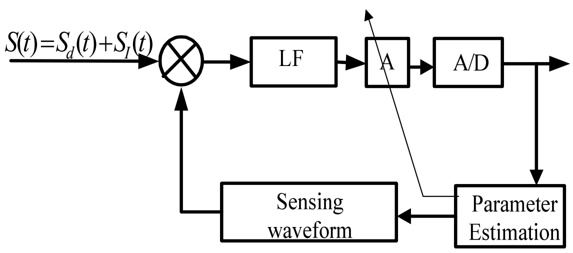

Fig. 1. The system structure of the adaptive strong interference suppression.

The working procedure of the system is as follows: when there is a strong interference signal, the system will attenuate the receiving signal first to keep the system in linear range. Then the receiving signal is sampled and sent to the digital part where the structure of the interference is estimated. Since the power of the interference is strong, the estimation will have high accuracy. And according to the results of estimation, the new sensing waveform is designed to be orthogonal to the interference and non-orthogonal to the weak signal as well. And the parameter that is used to produce the new waveform is fed back to the front-end to sense the receiving signal. Then the interference will be suppressed at the sampling time and the system can re-amplify the weak signal according to the requirement of the quantizing accuracy. The system works like an adaptive caving filter which can reject the random strong interference.

3. The Estimation of the Interference Signal and the Design of the Sensing Waveform

According to the above description of the system, there are two problems that are needed to be solved. One is the parameter estimation of the interference signal and the other is the design of the sensing waveform.

A. The parameter estimation of the interference signal:

The parameter we concerned in this system is the structure of the interference signal, i.e. the tight support Ψ_I of the signal. The definition of Ψ_I is as follows:

$$\Psi_I = \{\psi_n \in \Psi, n = 1,2,\ldots k_I : \|S_I(t)\|^2 = \sum_{n=1}^{k_I} \left|\langle S_I(t), \psi_n \rangle\right|^2 \}, \qquad (8)$$

where the interference signal is k_I - sparse and $k_I < M$.

OMP (Orthogonal Matching Pursuit) [9] is used to estimate the tight support of the interference signal in this paper and the procedure is:

1) $rf^{(0)} = \vec{y}$; $T^{(0)} = \phi, \Psi_I^{(0)} = \phi, L = 0$; where rf represents the residual and T represents the signal space. Ψ_I represents the tight support of the interference signal and the superscript L represents the iterative times.

2) If $L = k_I$, stop;

Else $\Theta_k = \arg[\max_{i=1,2,\ldots N} \langle \Theta_i, rf^{(L)} \rangle]$ and $\Theta_k = \Phi\psi_k$.

3) $L = L+1$, $T^{(L)} = T^{(L-1)} \cup \Theta_k$,

$\Psi_I^{(L)} = \Psi_I^{(L-1)} \cup \psi_k$, $rf^{(L)} = rf^{(L-1)} - T^{(L)}(T^{(L)})^{+}\vec{y}$

4) back to 2);

Then, Ψ_I which is got at the end of the iteration is the estimated tight support. Since the power of the interference is much stronger than the weak signal, the signal to noise ratio for the interference is high enough to get an accurate estimation of the tight support.

B. The design of the sensing waveform

The core of the system is the design of the sensing waveform. To satisfy (7), suppose that the new sensing waveform is Φ_{new} , then

$$\Phi_{new}\Psi_I = 0 \text{ , and } \Phi_{new}\Psi_I^{\perp} \ne 0 \qquad (9)$$

where $\Psi_I^{\perp} \cup \Psi_I = \Psi$, $\Psi_I^{\perp} \cap \Psi_I = 0$.

The design of Φ_{new} is as follows:

Since $\Theta = \Phi\Psi$, set those column vectors of Θ which are corresponding to Ψ_I to zeros, then we can get Θ_{new} and

$$\Theta_{new} = \Phi_{new}\Psi \qquad (10)$$

From (10):

$$\Phi_{new} = \Theta_{new}\Psi^{-1} \quad (11)$$

It can be proved that the new matrix Θ_{new} also satisfies RIP.

Let

$$\Theta_I = \Phi\Psi_I \quad (12)$$

For K and all K-sparse vectors $\vec{x}$:

$$\Theta_{new}\vec{x} = \Theta\vec{x} - \Theta_I\vec{x}_I , \quad (13)$$

where $\vec{x}_I \in R^{K_I}$ is the vector that is composed of those non-zero coefficients of the interference signal. And $\|\vec{x}_I\|_{\ell_2}^2 < \|\vec{x}\|_{\ell_2}^2$. Then,

$$\begin{aligned}\|\Theta_{new}\vec{x}\|_{\ell_2}^2 &= \vec{x}^T\Theta_{new}^T\Theta_{new}\vec{x} \\ &= \|\Theta\vec{x}\|_{\ell_2}^2 - 2\vec{x}^T\Theta^T\Theta_I\vec{x}_I + \|\Theta_I\vec{x}_I\|_{\ell_2}^2\end{aligned} \quad (14)$$

For Θ satisfies RIP，which means that any K columns of Θ are orthogonal to each other [10], then:

$$\vec{x}^T\Theta^T\Theta_I\vec{x}_I \approx \|\vec{x}_I\|_{\ell_2}^2 , \quad \|\Theta_I\vec{x}_I\|_{\ell_2}^2 \approx \|\vec{x}_I\|_{\ell_2}^2 \quad (15)$$

Bring (15) to (14):

$$\|\Theta_{new}\vec{x}\|_{\ell_2}^2 \approx \|\Theta\vec{x}\|_{\ell_2}^2 - \|\vec{x}_I\|_{\ell_2}^2 \quad (16)$$

$$\because \quad (1-\delta_K)\|\vec{x}\|_{\ell_2}^2 \le \|\Theta\vec{x}\|_{\ell_2}^2 \le (1+\delta_K)\|\vec{x}\|_{\ell_2}^2 \quad (17)$$

$$\therefore \quad (1-\delta_k-\rho)\|\vec{x}\|_{\ell_2}^2 \le \|\Theta_{new}\vec{x}\|_{\ell_2}^2 \le (1+\delta_K)\|\vec{x}\|_{\ell_2}^2 , \quad (18)$$

where $0 < \rho = \dfrac{\|\vec{x}_I\|_{\ell_2}^2}{\|\vec{x}\|_{\ell_2}^2} < 1$.

If only $|\rho + \delta_k| < 1$, Θ_{new} will satisfy RIP too.

4. Simulation

The performance of the proposed system is tested by simulations. And to distinguish between the desired weak signal and the strong interference, the weak signal does not be re-amplified after the interference cancellation for all the simulations.

Simulation 1: Noiseless Strong interference suppression. Two single tone signals are used and the frequencies are $f_I = 10\ MHz$ and $f_s = 25\ MHz$ respectively. The power ratio between the interference and the desired signal is $10\log P_I / P_S = 60\ dB$. The result is shown in Fig. 2.

The mean squared error between the original noiseless weak signal and the reconstructed signal after the interference suppression is:

$$\sigma^2_{\text{original weak signal-reconstructed signal}} = 3.7492\times10^{-4} \quad (19)$$

Simulation 2: Strong interference suppression in noise. Two single tone signals are used and the frequencies are $f_I = 10\ MHz$ and $f_s = 25\ MHz$ respectively. The power ratio between the interference and the aiming signal is $10\log P_I / P_s = 60\ dB$. The noise obeys $N(0,\sigma^2)$. And the SNR of the weak signal is 10dB. The simulation runs 100 times. An instance of the simulations is shown in Fig. 3.

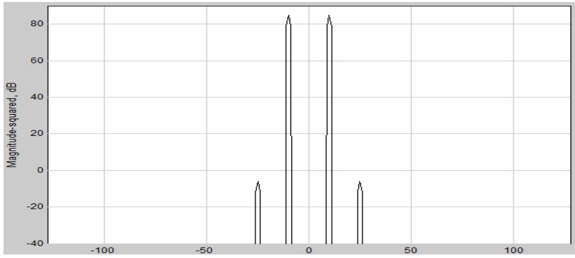

Fig. 2 (a). The double spectrum of the hybrid signal.

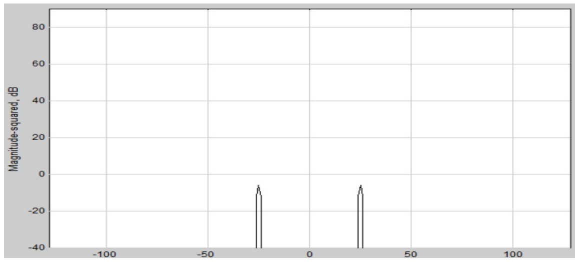

Fig.2. (b). The double spectrum of the reconstructed signal after the interference suppression.

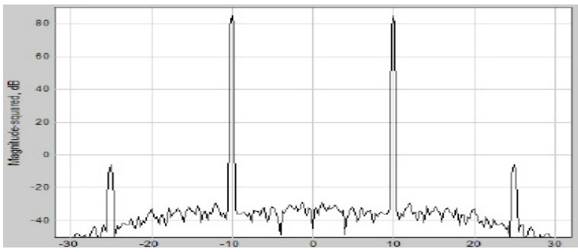

Fig. 3 (a). Double spectrum of the original hybrid signal.

Fig. 3 (b). Double spectrum of the reconstructed signal after the interference suppression.

The mean squared error between the original noiseless weak signal and the reconstructed signal after the interference suppression is

$$\sigma^2_{\text{original noiseless weak signal-reconstructed noiseless signal}} = 0.013 \quad (20)$$

Simulation 3: Noiseless strong interference suppression when both the interference and the weak signals are modulated. The data that are used to modulate the signals obey Bernoulli. The modulation method is QPSK and the roll off factor is 0.2. The carrier frequency of the interference is $f_I = 10\ MHz$ and the carrier frequency of the weak signal is $f_s = 2\ MHz$. $10\log P_I / P_s = 60\ dB$. The result is shown in Fig. 4.

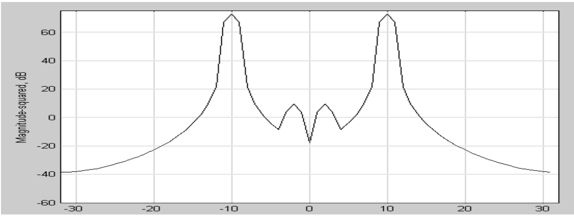

Fig. 4 (a). The double spectrum of the original hybrid signal.

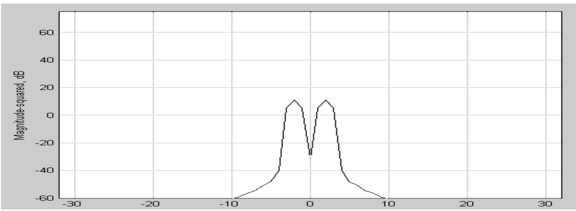

Fig. 4 (b). The double spectrum of the reconstructed signal after interference suppression.

Fig.4. Noiseless strong interference suppression

The mean squared error between the original noiseless weak signal and the reconstructed signal after the interference suppression is

$$\sigma^2_{\text{original weak signal-reconstructed signal}} = 9.8 \times 10^{-4} \quad (21)$$

Fig. 4 shows that even though the power ratio between the interference and the weak signals is as high as 60 dB, the system still can suppress the strong interference efficiently. The mean squared error between the original noiseless weak signal and the reconstructed signal after the interference suppression is as small as 9.8×10^{-4}, which means that the weak signal is preserved well during the interference suppression procedure and the reconstructed signal is propitious to the consequent signal processing.

5. Conclusion

A new adaptive strong interference suppression method based on analog-digital hybrid is proposed in this paper. By studying the tight support knowledge of the strong interference signal and adjusting the sensing waveform to be orthogonal to the interference, the method can suppress the strong interference before sampling and therefore the quantizing SNR for the weak signal can be improved. Theoretic analysis shows that the new sensing waveform satisfies RIP and will not affect the reconstruction. Simulations show that the method can suppress the strong interference before sampling effectively.

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