Signal Quality Assessment of Wireless Signal Based on Compressed Sensing

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Abstract. Detecting signal interference and assessing signal quality are essential tasks to ensure the normal communication within an area. As for traditional methods, we have to take field measurements after setting up a base station which needs to obtain huge data in low efficiency. Aiming at this particular problem, this paper proposed to assess signal quality by compressed sensing. Method of compressed sensing used in signal quality assessment is firstly discussed. After that, we introduced the specific process when assessing. At last the results of reconstructing the measured data and the predicted data separately shows that it could met the accuracy requirements of signal quality assessment.

Keywords: Wireless communication · Signal quality assessment
Compressed sensing · Field measurements

1 Introduction

Whether for military network or civil network, with the increase of network equipments, factors on interference of signal quality is more and more, especially in the complex electromagnetic environment, thus ensure the quality of wireless signals within range of base station has become a key problem [1]. In many complex environment, it is unrealistic for assessing signal quality with field measurement everywhere. In addition, before the erection of base station, if not predict the signal quality within range of it in advance, it may result in the risk of demolition and reerection because of a terrible erection position. Therefore we need to assess signal quality in advance until find out a good erection position. Thus, consider to sample sparse point and look for an appropriate algorithm to recover the signal quality of whole area. Compressed sensing theory has broken the traditional Nyquist Sampling Theorem. It does not consider the frequency characteristics of signals, but using the sparsity of signal in a transform domain,

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project the signal to a low dimensional space by using a measurement matrix irrelated with basis matrix, to reconstruct the signal by solving a convex optimization problem [2,3]. The reason of choosing this method is that nobody has used compressed sensing to assess signal quality through the literature retrieval, aimed to solve the contradiction between large amount of signal data and limited resources in complex network environment. Considering the detected signal strength is sparse under natural conditions, collecting a small number of signal strength data can recover the high-precision signal quality map by using reconstruction algorithm based on compressed sensing theory. This paper will introduce the key problems of compressed sensing and the method of detecting electromagnetic interference, then combine these two term, and construct a sparse model of signals to realize the signal quality assessment.

2 Signal Quality Assessment Method Based on Compressed Sensing

2.1 Construct Regional Sparse Model

The premise of compressed sensing is that signal can express sparsely under the selected basis matrix, so how to select a reasonable basis matrix makes the original signal become sparse after transformation is the key problem. For a one-dimensional signal $X \in R^N$, which can be linear representation as $X = \Psi S$ on the basis matrix $\Psi^T = [\Psi_1, \Psi_2, \ldots, \Psi_N]$, where S is called the sparse coefficient [4,5].

In the actual situation, assuming an area is grid distribution, then divide it into $I \times J$ homogeneous areas. Due to the electromagnetic wave signal has a spatial correlation, so each area after divided is considered as a sample point. After that, convert $I \times J$ regional matrix into one-dimensional $N \times 1$ matrix X($N = I \times J$), to facilitate the measurement matrix to measure. Considering the sparsity of electromagnetic wave signal, we chose the Fast Fourier Transform as a basis matrix. Specifically, if S is the two-dimensional Fourier Transform of X, it can get $s = Wx$, with $s = vec(S)$, $x = vec(X)$. (If V is a $k \times 1$ matrix, then $vec(V)$ means the $kl \times 1$ vector stacked by columns of V, that is $vec(V) = [v_{11}, \ldots, v_{l1}, \ldots, v_{1k}, \ldots, v_{kl}]^T$). W is the Discrete Fourier Transform matrix $W[m, k] = e^{-j2\pi mk/l}$, s is sparse.

2.2 Construction of the Unit Measurement Matrix

The construction of measurement matrix is the core problem of compressed sensing. One of the focuses is to measure and preserve most of the useful information of original signal, so that the reconstruction and recovery are meaningful. Otherwise once the information is missing while doing measurement, we can foresee the recovery signal must be far from the original signal. Another focus of constructing measurement matrix is to ensure it is not related with the vast majority of basis matrix, and can be used for the majority of compressed signal [6,7].

Currently, the measurement matrix which satisfy these conditions and has been widely applied includes Fourier matrix, Bernoulli random matrix, Gaussian random matrix, etc.

Combined with the previously constructed sparse model, this paper uses a special measurement matrix transformed by the unit matrix [8], specific steps are as follows:

1. Ramdomly disturbing a unit matrix of $N \times N$ and extract M rows, get a ϕ matrix of $M \times N$ (a subset of unit matrix), 1 only shows up one time in each row with others are all 0.
2. Multiplying ϕ by X, then get the matrix Y of $M \times 1$ after measurement. Due to the characteristics of ϕ, its each row multiplied by X makes only one value be retained, the others are 0. It means we only select one area from X, and the characteristics of ϕ would determine the selection will not be repeated later.

2.3 Signal Reconstruction Algorithm

When reconstruct the signal, the length of measurement value M is far less than the length of original signal N, thus the reconfiguration problem is essentially a problem of solving underdetermined equations, that is the minimum 0 norm problem [9]. Such as shown in formula (1).

$$min\|\Psi^T X\|_0 \qquad s.t.\, AX = \phi\Psi X = Y \tag{1}$$

Superficially, it seems to be a NP hard problem. But because the signal is compressible and it has been proved that if the measurement matrix meet the property of RIP(Restricted Isometry Property), this L0 problem can be transformed to L1 problem by Candes, Tao and Donoho, such as formula (2) shows.

$$min\|\Psi^T X\|_1 \qquad s.t.\, AX = \phi\Psi X = Y \tag{2}$$

Based on the above problems, new reconstruction methods are proposed continually. Now it mainly including greed tracking algorithm, convex optimization algorithm and reconstruction algorithm based on bayesian framework, etc. [10].

Considering the greedy tracking algorithm has characteristics of high recovery rate and it is easy to implement, OMP (Orthogonal Matching Pursuit), as the reconstruction algorithm, is chosen to prove the validity of the project [11,12]. According to the selected areas of the observation matrix we can get these Y signal strength values, then reconstruct the signal of $I \times J$ by OMP.

3 Signal Quality Assessment

For a large scale of communication network, there may be multiple base stations, radios and other communication equipments in an area. In this complex electromagnetic environment, as the communication network topological structure and spectrum allocation been finished, there may not have a good communication quality within the scope of cover. Thus, assessing the quality to ensure the rationality of the communication network construction is necessary.

3.1 Electromagnetic Wave Propagation Attenuation Analysis

In actual communication, considering the attenuation between transmitting end and receiving end because of complex terrain, the transmission process is more complex. Thus the electromagnetic wave model of free space transmission must be modified based on these factors. According to the result of field measurement, compared the predicted results of deterministic model (ITU-RP.526) with the semi empirical and semi deterministic model (Longley-Rice), it shows that the predicted result of ITU-RP.526 model is closer to the actual result as shown in Fig. 1. So ITU-RP.526 model can take the place of field measurement to compare with reconstructed signal. Specific steps are as follows:

1. To start with, analyze the ground type and determine the irregularity of the terrain with Δh. The terrain is smooth if $\Delta h \leq 0.1 \times R_{max}$, otherwise exists obstacles, where Δh is the height difference between transmitter and receiver, R_{max} is the maximum radius of the first Fresnel region on the propagation path.
2. Suppose the terrain is smooth, then judge whether the horizon is blocked with $d_{los} = \sqrt{2a_e}(\sqrt{h_1} + \sqrt{h_2})$. If the distance between transmitter and receiver $d \geq d_{los}$, so calculate the diffraction attenuation by out of horizon path, otherwise using the horizon path.
3. If there are obstacles on the terrain, then judging the type of obstacle firstly, which is divided into blades and circles. After that, calculate the number of obstacles.
4. Finally, for the different types of obstacle models, calculate the diffraction attenuation L_p of electromagnetic wave refer to the ITU-RP.526 proposal [13].

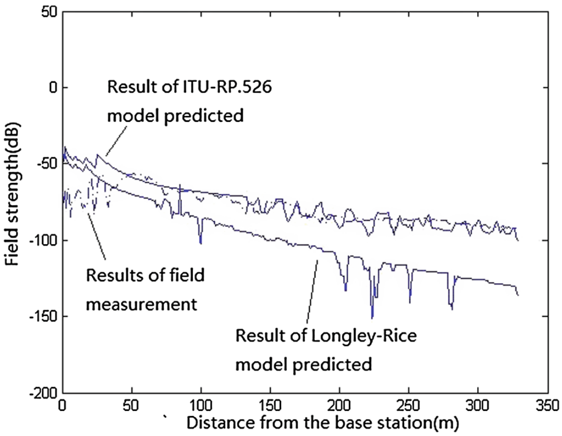

Fig. 1. The result of comparison between field measurements and prediction of simulation models.

3.2 Frequency Deviation Inhibitory Factor

For a large scale of communication network, multiple base stations are usually set up in an area. Because of the limitation of frequency resources, different base stations may be assigned to different working frequencies. It may cause interference signals to fall into the receiver's frequency band which can affect the signal quality that can hardly communicate. Therefore, it is neccessary to introduce the frequency deviation inhibitory factor(OCR), which is used to measure the suppression of the receiver's selective curve to the interference spectrum [14]. It is defined as formula (3):

$$OCR(\Delta f) = -10 \log \frac{\int_{-\infty}^{\infty} P(f)|H(f+\Delta f)|^2 \, df}{\int_{-\infty}^{\infty} P(f) \, df} \tag{3}$$

Then, the signal quality can be assessed by formula (4).

$$SNR = P_d - \sum_{i=1}^{n} P_i \quad (dB) \tag{4}$$

The P_d and P_i are according to formula (5) to calculate.

$$\begin{cases} P_i = P_t + G_t + G_r - L_p - OCR(\Delta f) \\ P_d = P_t + G_t + G_r - L_p \end{cases} \tag{5}$$

where the P_i is interfering signal strength, P_d is useful signal strength, P_t is transmitting power, G_t is transmitter antenna gain, G_r is receiver antenna gain, L_p is attenuation values, OCR is frequency deviation inhibitory factor.

4 Experiment and Simulation Analysis

4.1 Simulation of Field Measurements Data

In order to verify the correctness of the proposed signal quality assessment scheme based on compressed sensing, the actual data measured by a certain area is used to take experimental comparison.

In Table 1, the base station is located at $80.94219°E$, $41.07261°N$, with the antenna basic parameters of the down-tilt angle is 2°, the azimuth is 150°, the height is 58 m, and the carrier power is 150 W. The original data and the reconstructed result are shown in Fig. 2.

Because the data of field measurements is useful signal strength, thus it can be used to reconstruct the SNR. From the Fig. 3, it can be seen that as the number of samples increases, the error of the reconstruction decreases, although there are some cusps on the curve caused by bad samples. When the sampling point is more than 80%, the original signal is basically perfectly reconstructed, but at the cost of time and resource.

Table 1. Part of signal strength of field measurements

Longitude ($^\circ E$)	Latitude ($^\circ N$)	Distance from the base station (m)	Signal strength (dB)	Predicted results (dB)	Reconstructed results (dB)
80.94202000	41.07396167	151	−80.13	−79.50	−77.43
80.94194667	41.07422833	182	−59.69	−56.71	−62.85
80.94190500	41.07436333	197	−57.63	−58.37	−54.71
80.94185667	41.07450333	214	−57.00	−59.58	−56.53
80.94174167	41.07479167	247	−59.50	−62.20	−61.88
80.94167333	41.07494167	265	−63.67	−61.74	−66.04
80.94159833	41.07509333	284	−72.13	−74.51	−74.85
80.94151500	41.07524833	302	−78.64	−77.98	−75.90
80.94132667	41.07556667	342	−67.29	−70.21	−71.60
80.94122333	41.07573000	363	−65.00	−66.14	−63.53

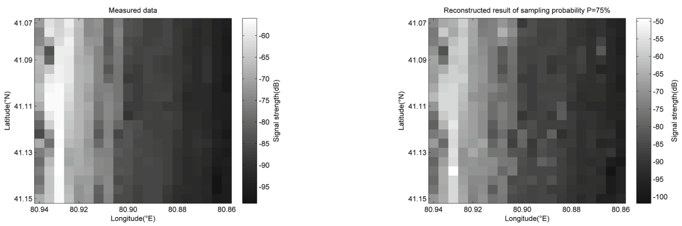

Fig. 2. Reconstructed result with 75% sampling point, Pe = 0.0287.

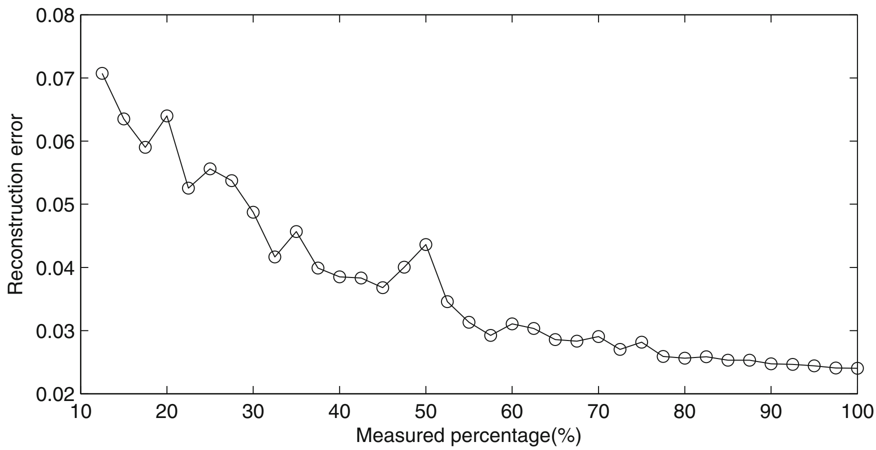

Fig. 3. Sampling proportion versus reconstruction error.

4.2 Simulation of Predicted Data by ITU-RP.526 Model

In order to ensure the practicality of the scheme, the signal quality of the surrounding area can be estimated before set up the base station, and verify it by the ITU-RP.526 model. The result shows as Fig. 4.

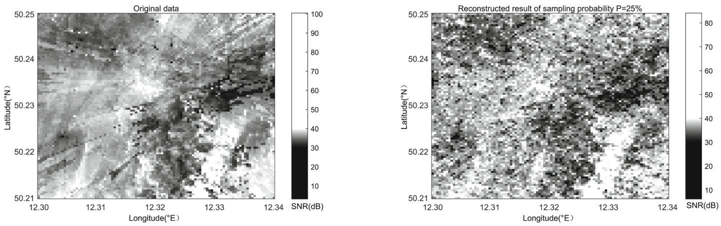

Fig. 4. Reconstructed result of prediction of ITU-RP.526 model, Pe = 0.0737.

The jammers are located at

1. $12.31342°E$, $50.23786°N$, frequency is 150.42 MHz, power is 40 W.
2. $12.30368°E$, $50.24468°N$, frequency is 150.61 MHz, power is 30 W.
3. $12.30154°E$, $50.22156°N$, frequency is 150.35 MHz, power is 20 W.

The useful receiver is located at $12.33161°E$, $50.23611°N$, frequency is 150.55 MHz, power is 30 W.

The results show that when sampling points are 25%, it is already clear to distinguish the area of high SNR from low SNR. It meets actual demand and proves the correctness of the scheme.

5 Conclusion

The paper introduced an estimate method based on compressed sensing. The method can solve the enormous data problems benefits from the advantage of compressed sensing, which works well on data reconstruction and compression. The results show that the new algorithm meets our demand both in field measurement and model prediction. The future work is to solve the problem of the reconstruction error caused by terrain mutation.

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