The Research of Wireless Channel Feature Extraction and Channel Discrimination

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Abstract

In different environments, there are some differences characteristics of the wireless channel. These differences are called "fingerprint". Extracting the "fingerprint" characteristics of different channels in different environment is very important to the development of wireless communication. This paper is focus on the problem of "fingerprint extraction". Through wireless channel signal inversion and K-means clustering and compressed sensing, establishing an adaptive clustering model. And then establish a reasonable "fingerprint" feature with the existing data and relevant physical background. Use MATLAB to solve the model and verify the accuracy. Computer verification and comparison analysis show that this model can be used to identify the wireless channels with high accuracy.

Keywords: wireless channels; Feature extraction; compressed sensing; K-means clustering

1 Introduction

In mobile communication, some invisible electromagnetic pathway, called wireless channel, existed between the transmitter and the receiver. The characteristics of wireless channel seriously affect the performance of the mobile communication system, so the research of wireless channel is the foundation of the mobile communication research.

The wireless signal transmission environment between transmitter and receiver is extremely complex. First of all, the radio will emerge not only the dispersion consumption as the propagation distance increases, but also the 'shadow effect' caused by the cover of terrain and buildings. In addition, more reflection will produce multipath signals, whose amplitude, phase and arrived time are not identical; their mutual superposition can produce level fast fading and delay spread. Secondly, mobile communications often take place in a fast moving, this will cause the Doppler frequency shift, generate random frequency modulation, and make waves propagation properties happen fast random fluctuation. Therefore, wireless signal transmission environment is changed with time, environment and other external factors [1-3].

Wireless channel has some differentiation called 'fingerprint' under different environment. To extract and modeling these fingerprints is an extremely important role for the development of wireless communication.

Many scholars are analyzed the characteristic of wireless channel. A new wireless channel model with phase of parabolic characteristics is proposed and analyzed[4], according to the actual channel dispersion phenomenon. But the channel dispersion phenomenon occurs in the specific geographical environment, it is not a universal. A new time delay estimation executing the maximum likelihood rule under multipath environment is proposed[5], the global maximum of compress likelihood function is calculated under the small amount of calculation, and then to make distinctions for channel. When

ISSN: 2233-7857 IJFGCN Copyright © 2016 SERSC the number of paths is small, the maximum likelihood algorithm has strong ability of noise suppression and fast convergence, but in the case of path number greater than 4, the simulation results show that the convergence speed is very slow, and the noise suppression ability becomes poor, channel estimation precision is lower. For defects of Jakes simulator and its modified simulator, a new Jakes simulation model is proposed[6], which can be used for the modeling of frequency selective channel, such as UWB channel. It's using range is relatively narrow, for other channel characteristic analysis of the effect is not ideal.

In the actual wireless channel, the transmission of electromagnetic wave is affected by scattering (including reflection and diffraction), propagation distance, multipath time delay and other issues, taking single feature to accurately distinguish channels is very difficult, and so it needs multiple characteristics jointing to distinguish. For this, on the basis of the prior model and test data, this article extract differentiation characteristics of wireless channel under the different scenarios or different regional, analyze and summarize the mathematical model of 'fingerprint', and then give the clear mathematical description, finally validate the rationality model of feature extraction using the measured data packets.

2. Feature Extraction of Wireless Channel

Considering effects of multipath coefficients and multipath time delay in engineering, on the premise of guarantee the accuracy, the discrete linear system is commonly used for the wireless channel modeling [7]. In the model, the signals and multipath coefficients are all plural, ideal channel measurement can be understood as the system unit sequence response acquisition, that is to obtain the received signal after the unit pulse signal $\delta(k)$ transmits from wireless channel. The above measurement results of the ideal channel are expressed by the formula (1):

$$h[k] = \sum_{l}^{L-1} h_{l} \cdot \delta[k - \tau_{l}], k = 0, 1 \cdots, K - 1, K \ge \max_{l} \{\tau_{l}\}$$

$$\delta[k] = \begin{cases} 0, k \ne 0 \\ 1, k = 0 \end{cases}$$

$$(1)$$

At the current moment, k is the number of discrete signal, K is the samples number, L is the paths number, usually are plural, hl is the 1-th channel coefficient, τ_i is the 1-th channel time delay, h[k] denotes the whole channel. These above variables have the character of time-varying.

In the practical wireless communication system, the transmit signal will be affected by various kinds of interference, in order to ensure the quality of signal transmission, the filters are usually added in the transmitter and the receiver, which will cause the ideal channel measurement results h[k] cannot be directly obtained. Existing theory has been proved that the effect on the channel measurement caused by filter, can be expressed by function g[k], the channel measurement results is shown in type (2):

$$r[k] = \sum_{m=0}^{M-1} h[k-m] \cdot g[m], k = 0, 1, \dots, K-1$$
 (2)

Where, M is the length of filter, the samples number of g[k]. Because of time-varying of the channel and the measurement noise introduced by measurement, so the real channel measurement results of different time and their corresponding wireless channel are expressed respectively by type (3) and type (4):

espectively by type (3) and type (4):

$$r[k,n] = \sum_{m=0}^{M-1} h[k-m,n] \cdot g[m] + u[k,n], k = 0,1\cdots, K-1, n = 0,1\cdots, N-1$$

$$h[k,n] = \sum_{l=0}^{L-1} h_l[n] \cdot \delta[k-\tau_l[n]] \cdots$$
(4)

$$h[k,n] = \sum_{l=0}^{L-1} h_l[n] \cdot \delta[k - \tau_l[n]] \cdot \cdot$$
 (4)

Where, n is the tested sample No, hl[n] is the 1-th channel coefficient, $\tau_l[n]$ is the time delay of the 1-th channel, u[k,n] is the Gaussian noise, r[k,n] is the real received signal, from r[k,n] can obtain the time-varying channel h[k,n].

3. Adaptive Clustering Model Establish

3.1. Wireless Channel Signal Based on Compressed Sensing

Using the filter g[m] and the channel observed signal r[k] to solve h[k]. G is used to express g[m]. In order to obtain the whole r[k,n], the solution of a set of equations rn=G*hn+un is needed at each sample moment, that is:

$$\begin{bmatrix} r(0,n) \\ r(1,n) \\ \vdots \\ r(K-2,n) \\ r(K-1,n) \end{bmatrix} = \begin{bmatrix} g(1) & g(0) \\ g(2) & g(1) & g(0) \\ \vdots & \vdots & \ddots & \vdots \\ g(M-1) & g(M-2) & \dots & g(1) & g(0) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ g(M-1) & g(M-2) & \dots & g(1) & g(0) \\ \vdots & \vdots & \vdots & \vdots \\ g(M-1) & g(M-2) & \dots & g(1) & g(0) \\ \vdots & \vdots & \vdots & \vdots \\ h(K-2,n) \\ \vdots & \vdots & \vdots \\ h(K-1,n) \end{bmatrix}$$

In the above function, the vector rn and the matrix G is known, the vector un is Gaussian white noise. From Figure 1, it can be seen that G is a highly morbid matrix, its solution is very difficult.

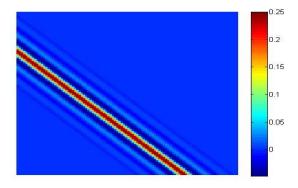


Figure 1. The Morbid Matrix G

Based on the above, this article uses the compressed sensing principle to convert problem[8-9]. Compressed sensing principle shows that for the under-determined equations Ax=b of x=[x0,x1,...,xK-1]T, the problem can be translate into solving optimization problem under certain conditions[10-11]. The basic model is as follows:

$$\begin{aligned} \min \|x\|_1 \\ s.t. \\ \left\|Ax - b\right\|_2^2 < \varepsilon \end{aligned}$$
 Where, $\|x\|_1 = \sum_{k=1}^{K-1} \left|x_k\right|$, $\|x\|_2 = \sqrt{\sum_{k=1}^{K-1} x_k^2}$ \circ

This model has made a very wide range of applications in the information science and image reconstruction [12-13].

The above model is optimized in this paper, combining the difference operator D and discrete signal to replace x, the optimization model is established as follows:

$$\begin{aligned} & Min \|Dh\|_{_{1}} \\ & s.t. \\ & \|Gh-r\|_{_{2}}^{2} < \varepsilon \end{aligned}$$

For discrete signal h[0], h[1], ..., h[K-1], Dh is h[1]-h[0],h[2]-h[1],...,h[K-1]-h[K-2].

Take scenario 1 channel 1 as examples, take the h[k,1] into the function $r_1 = k \cdot h_1$. compared with the sampling data, we can see that this method is valid. The comparison between the real and imaginary part of the results is shown in Figure 2.

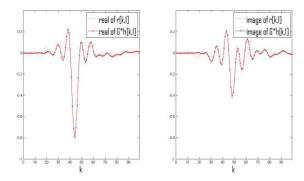


Figure 2. The Real and Imaginary Part of Sample Signal

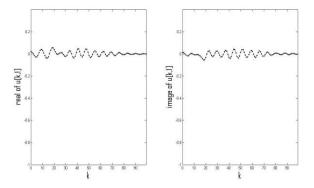


Figure 3. The Real and Imaginary Part of Noise u[k,1]

After the above steps, the noise signal u[k,1] can be obtained, whose real part and imaginary part are shown in Figure 3, and its frequency histogram is shown in Figure 4. We can see that the extracted noise signal is consistent with u with complex Gaussian white noise, which reflect the validity of the model and the accuracy of results.

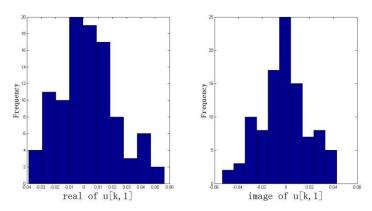


Figure 4. The Frequency Histogram of Noise u[k,1]

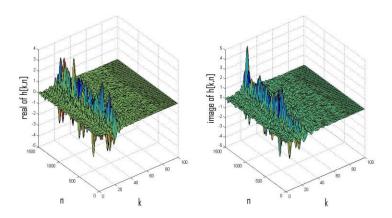


Figure 5. h[k,n] of Scene 1 Channel 1

The h[k,n] of each channel each scene is resolved in turn, the all data h[k,n] of scene 1 channel 1 are shown in Figure 5.

3.2 The fitting of ideal signal δ

Through the optimization model to extract h[k, n], and then solve integer L[n], plural $h_l[n]$, integer $\tau_l[n]$, etc, such as the equation set shown in (4):

$$h[k,n] = \sum_{l=0}^{L[n]-1} h_l[n] \cdot \delta[k - \tau_l[n]], k = 0,1, \dots K - 1$$
(4)

In ideal conditions, $\{\tau_l[n]\}_{l=0}^{L-1}$ is different from each other, it is only L[n] non-zero element in h[k,n], which is the value of $h_l[n]$, It is means that $L[n] = |\{k \mid h[k,n] \neq 0\}|$ and $h_l[k,n] = h[\tau_l[k,n],n]$. $L[n], \tau_l[n]$ and $h_l[k,n]$ can be con-firmed by non-zero number and position in h[k,n]. The ideal condition is shown in Figure 6.

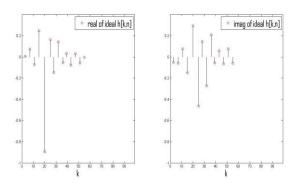


Figure 6. The Real and Imaginary Part of Ideal h[k,1]

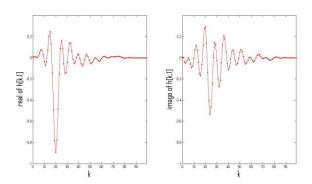


Figure 7. The Real and Imaginary Part of Real h[k,1]

In fact, h[k,n] only has approximate form, that is δ function is not accurately, unable to find out permanent solution, shown in Figure 7. The integer L[n], $\tau_l[n]$ can be combined to process optimal solution and compare options of $h_l[n]$, which is translated into the integer programming problem shown as the following type (5):

$$\underset{L \in S_L, \tau_l \in S_{\tau}, h_l \in C}{\arg \min} \sum_{k=1}^{K-1} \left| h[k, n] - \sum_{l=0}^{L[n]-1} h_l[n] \cdot \delta[k - \tau_l[n]] \right|^2$$
 (5)

 S_L is L collection of all possible values, S_τ is τ_L collection of all possible values, C is for the plural sets. Obviously this model requires a large number of operations, it will take up a lot of system resource in a larger data samples. Consider the approximate solution, take h[k,n] as the sum of several approximate signal δ , determine the crest and trough location to do subsequent solution, namely to fitting method is as follows:

Input: channel data h[k,n], Energy duty ratio η

Output: the path number L[n], multipath time delay $S_{\tau}[n]$, multipath coefficient $S_h[n]$.

1) Initial
$$S_{\tau} = \emptyset$$
, $S_h = \emptyset$,

$$S_0 = \{k \mid Dh[k,n] * Dh[k+1,n] < \varepsilon\} \ E_0 = \sum_{k \in S_0} |h[k,n]|^2 \ , \ \text{ turn to 2})$$

2)
$$k_{\text{max}} = \arg \max_{k \in S_0} |h[k, n]|$$
, turn to 3)

3)
$$k_{\text{max}} \rightarrow S_{\tau}$$
, $S_0 = S_0 \setminus \{k_{\text{max}}\}$

$$\begin{split} &h[k_{\max},n] \to S_h, \text{ turn to 4})\\ &4) \text{ If } &\sum_{k \in S_r} &|h[k,n]| < \eta E_0 \text{ , turn to 2}); \text{ else turn to 5}) \end{split}$$

5) $L = |S_{\tau}|$, end

The peaks and troughs of the real and imaginary part of $h_l[k,n]$ are shown in Figure 8.

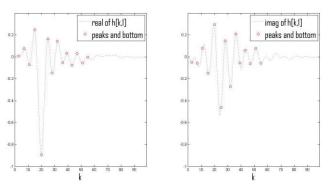


Figure 8. The Peaks and Troughs of the Real and Imaginary Part of h[k,n]

3.3. Analysis of the Rationality of Fingerprint Characteristics

There may be one or more features in a wireless channel. For example, the mean value of the number of channel paths L[n]. Standard deviation of the number of channel paths L[n]. Real part signal dominant frequency of main channel path coefficient $h_0[n]$ and so on. Now sort out the possible features and analyze the rationality of it.

1) μ ----the mean value of the number of channel paths L[n]

Analysis: this feature can reflect the complexity of the scene. For example, in the environment of indoor or City Center, a series of reflection and diffraction will occur after the signal is sent out. At this point, the value of μ is larger; on the contrary, in some open areas, it is smaller.

2) δ ----Standard deviation of the number of channel paths L[n]

Analysis: this feature can reflect the dynamic degree of the scene. Because δ indicates the extent of the volatility of L[n]. The value reflects the number of paths directly. If the value of δ is larger, it can reflect the high dynamic degree of the scene from a certain degree (Such as motion scene). If the value is small, it can be reflected the low dynamic scene from a certain degree (such as static scenes).

3) rf_1 ----Real part signal dominant frequency 1 of main channel path coefficient $h_0[n]$ Analysis: this feature can reflect the dynamic degree of the scene from the changing frequency of the channel main path. The larger value indicates that the real part of $h_0[n]$

is changing fast and show that the scene is more complex or the scene has high dynamic degree. On the contrary, the change is slow, the scene is simple or has low dynamic degree.

- 4) rf_2 ----Real part signal dominant frequency 2 of main channel path coefficient $h_0[n]$ Analysis: Has the same meaning with the (3).Related to the complexity or dynamic degree of the scene.
- 5) if_1 ----Imaginary part signal dominant frequency 1 of main channel path coefficient $h_0[n]$

Analysis: Has the same meaning with the (3). Related to the complexity or dynamic

degree of the scene.

6) if₂----Imaginary part signal dominant frequency 2 of main channel path coefficient $h_0[n]$

Analysis: Has the same meaning with the (3).Related to the complexity or dynamic degree of the scene.

7) p_1 ----Coefficient of one degree term of linear fitting of the channel main path delay $\tau_0[n]$.

Analysis: if the main path is invariant, this feature is related to the moving speed of the signal receiving terminal in the scene. When the absolute value of p_1 is large, the receiver moves faster; otherwise, the speed is slow.

8) p_0 ----Linear fitting constant term of the channel main path delay $\tau_0[n]$.

Analysis: if the main path is unchanged, the feature is related to the distance from the signal receiving terminal to the sending terminal in the scene. The absolute value is larger, the distance is larger; otherwise, the distance is smaller.

9) S_r ----Linear fitting residual error of channel main path delay $\tau_0[n]$.

Analysis: if the main path unchanged, this feature is related to the rate of change of the signal receiving terminal. If the value of S_r is larger, the speed of receiving terminal is not evenly. otherwise, the speed is evenly.

For each feature, it is required to have a certain ability to distinguish each scene. The scene is distinguished by a large number of "fingerprint" characteristics, a certain character does not have the ability to distinguish completely, But a certain characteristic should be able to reflect the ability of local discrimination to some extent. For example, a feature has the ability to distinguish the classify A (Scene 1), class B (Scene 2 and 3). The combined effect of a certain number of features (possibly nonlinear) has the ability to distinguish classify C (Scene 2), class D (Scene 1 and scenario 3). Therefore, this paper establishes the evaluation index of features—— separating capacity.

Take the comprehensive action f of some features as an example.In I samples (ordinal numbers from 1 to 15), the values were $f[1], f[2] \cdots f[I]$. The serial number set S_z contains all the sample numbers that belong to the z of the scene. $z \in Z = \{1, 2, \cdots, J\}(J=3)$. Based on the above, establish type(6) to measure the ability of distinguish a number of scenes.

$$E_{3} = \frac{1}{\sum_{\substack{i \neq j \\ i, j \in Z}} 1} \sum_{\substack{i \neq j \\ i, j \in Z}} \left| \frac{\sigma_{i} + \sigma_{j}}{\mu_{i} - \mu_{j}} \right|$$
(6)

Where $\mu_z = \frac{1}{|S_z|} \sum_{s \in S_z} f_s$, $\sigma_z = \frac{1}{|S_z|} \sum_{s \in S_z} |f_s - \mu_z|$. The smaller value of E_3 , the greate-r

difference among different scenarios.

Sometimes scenes 2 and Scene 1 may have the same characteristics, Using those features to distinguish the different scenes, sometimes maybe cause miscarriage of Justice. This will be very difficult to separate all the scenes. So this paper designs a method of global distinguish. That is: if there are scenes A, B, C, the algorithm can be based on a certain characteristic separate A from B and C, and so on. Establishing a model to describe the above separating capacity. It is shown as the following type (7).

$$E_2 = \frac{1}{|Z|} \sum_{i \in Z} \left| \frac{\sigma_i + \sigma_i'}{\mu_i - \mu_j'} \right| \tag{7}$$

$$\mu_z = \frac{1}{\left|Z \setminus S_z\right|} \sum_{s \in Z \setminus S_z} f_s \qquad \sigma_z = \frac{1}{\left|Z \setminus S_z\right|} \sum_{s \in Z \setminus S_z} \left|f_s - \mu_z\right|$$

The smaller value of E_2 , the greater difference among different scenarios. Add weights to E_2 and E_3 . Using different weighted values in different scenarios. And finally establish the evaluation index of characteristics. As shown in type (8).

$$E = \frac{\alpha E_2 + \beta E_3}{2} \tag{8}$$

Where $\alpha \setminus \beta \in (0,1), \alpha + \beta = 1$. The smaller the value, the stronger the ability to distinguish different scenes.

According to the above analysis and results. Extracting all the features of a total of 15 channels in 3 scenes

by MATLAB programming. Get 15 sample data and their scene. As shown in Table. 3.

| Sample number | Ми | Sig | rf_1 | rf_2 | if_1 | if_2 | p_1 | p_0 | S_r | Scene |
|------------------|------|------|--------|--------|--------|--------|-------|-------|-------|-------|
| 1 | 7.95 | 1.00 | 268.75 | 481.75 | 268.75 | 481.75 | 3.67 | 21.76 | 1.91 | 1 |
| 2 | 8.63 | 0.99 | 273.25 | 477.25 | 273.25 | 477.25 | 3.75 | 29.24 | 1.12 | 1 |
| 3 | 8.46 | 0.98 | 267.25 | 483.25 | 267.25 | 483.25 | 4.03 | 26.87 | 1.15 | 1 |
| 4 | 8.51 | 1.04 | 269.25 | 481.25 | 269.75 | 480.75 | 4.54 | 21.34 | 2.02 | 1 |
| 5 | 8.18 | 1.02 | 272.25 | 478.25 | 271.75 | 478.75 | 3.96 | 18.99 | 1.58 | 1 |
| 6 | 9.94 | 1.24 | 148.75 | 601.75 | 148.75 | 601.75 | 1.77 | 21.66 | 5.03 | 2 |
| 7 | 9.39 | 1.15 | 154.75 | 595.75 | 154.75 | 595.75 | 2.23 | 25.78 | 1.43 | 2 |
| 8 | 9.18 | 1.18 | 157.75 | 592.75 | 157.75 | 592.75 | 2.02 | 20.43 | 3.05 | 2 |
| 9 | 8.62 | 1.05 | 140.75 | 609.75 | 140.75 | 609.75 | 1.55 | 24.82 | 1.13 | 2 |
| 10 | 8.58 | 1.06 | 146.25 | 604.25 | 146.25 | 604.25 | 1.76 | 26.77 | 0.96 | 2 |
| 11 | 8.93 | 1.25 | 106.75 | 643.75 | 106.25 | 644.25 | 3.82 | 25.34 | 2.75 | 3 |
| 12 | 9.79 | 1.28 | 130.25 | 620.25 | 129.75 | 620.75 | -3.15 | 33.34 | 2.96 | 3 |
| 13 | 8.85 | 1.29 | 148.25 | 602.25 | 148.75 | 601.75 | -2.32 | 39.72 | 2.14 | 3 |
| 14 | 8.52 | 1.14 | 166.75 | 583.75 | 166.25 | 584.25 | 6.09 | 20.63 | 3.47 | 3 |
| 15 | 8.54 | 1.23 | 158.25 | 592.25 | 161.25 | 589.25 | 4.09 | 29.19 | 2.89 | 3 |

Table 1. 15 Samples and Classification Results

3.4. K-Nearest Neighbor (KNN) Classification Model Based on Local Weighted Mean

K nearest neighbor is a non-parametric classification model proposed by Cover and Hart. After many years development, it has become one of the most widely used classification models [14,15]. The main idea is: the sample set $S=\{xi\}$ and the classification label $c\{i\}$ for a sample x to be classified, the first is to find out the training sample set Nk(x) which is the most close or similar to x with the known class label, and then to determine the sample category according to the category label of training samples. This model can be expressed as the optimal form of the following (8):

$$C(x) = \underset{z \in Z}{\arg\max} |S_z| \tag{8}$$

 $C(x) = \underset{z \in Z_c}{\arg \max} |S_z|$ $\text{Where } S_z = \{x_j \in N_k \mid c_j = z\}, \quad N_k(x) = \{x_j \in |V_j(x)| < K\}, \quad V_j(x) = \{x_\alpha \in S \mid |x_\alpha - 1| < |x_j - x|\}. \quad c_j \text{ is the class of } S_j = \{x_j \in N_k \mid c_j = z\}, \quad N_k(x) = \{x_j \in |V_j(x)| < K\}, \quad V_j(x) = \{x_\alpha \in S \mid |x_\alpha - 1| < |x_j - x|\}.$ samples $x_i^{[16,17]}$.

The KNN classification model is not required to know the distribution function of the

samples to be distinguished, with the characteristics of direct viewing, no prior knowledge and no teacher learning, it is widely used in clustering analysis. Its disadvantage is that the sample's imbalance may cause a classification error [18]. In order to avoid the disadvantages of the model in the small sample case, this paper establishes a new model, which is based on the local weighted mean value, shown in (9):

$$C_{w}(x) = \arg\max_{Z \in Z_{c}} w_{z}(x) |S_{z}|$$
(9)

with the disadvantages of the model in the small sample case, this paper establishes a tew model, which is based on the local weighted mean value, shown in (9):
$$C_w(x) = \underset{Z \in Z_c}{\arg \max} w_z(x) |S_z| \qquad (9)$$

$$wz(x) = \frac{1}{\left|x - \frac{1}{|S_z|} \sum_{x_j \in S_z} x_j\right|} \qquad \text{denotes the weight of } S_z \text{ in } N_k(x). \text{ Thus, even the training same size is small, it also can effectively avoid error classification because of the uneven$$

ple size is small, it also can effectively avoid error classification because of the uneven distribution of new samples.

4. Model Verification

In this chapter, using the observation signal inversion model based on compressed sensing and the test data samples in two real channels, the above model is verified. The inversion operation for r[k,n], get the ideal signal data h[k,n], at n=1, the real part and the imaginary part is respectively shown in Figure 9 and Figure 10.

The data are all from real signal acquisition.

Packet 1: provides testing data of three scenes, each scene consists of five real channel data, each channel contains 1500 test samples in one second.

Packet 2: the scenes are same as packet 1, but contains two real channel measurements, respectively named test data 1, test data 2.

Using the observation signal inversion model based on compressed sensing using packets from known 2 set two real channel measurement data samples to test for the model, carried out in accordance with the model of data processing step by step. The inversion operation in the first place, get the ideal signal data, at the time, real part and imaginary part as shown in figure 9 and 10, respectively.

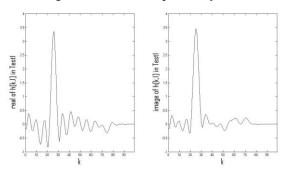


Figure 9. The Real and Imaginary Part of Test Sample 1

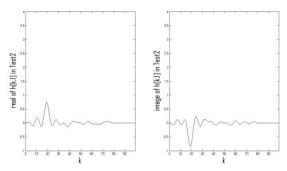


Figure 10. The Real and Imaginary Part of Test Sample 2

Using the δ fitting algorithm, we can obtain L[n], $h_l[n]$, $\tau_l[n]$, the fitting results of test sample 1 and sample 2 at n=1 are shown in Figure 11 and Figure 12.

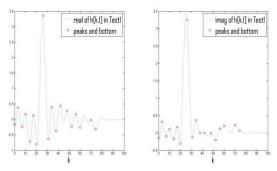


Figure 11. The Fitting Results of Test Sample 1

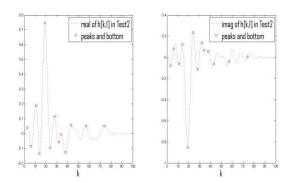


Figure 12. The Fitting Results of Test Sample 2

For the test sample 1, L=18, τ_1 , h_1 is given by Table.2 and Table.3.

Table 2. The Time Delay τ_r of Test Sample 1 at n=1

| $	au_l$ | 27 | 21 | 15 | 32 | 35 | 4 | 43 | 39 | 75 |
|---------|----|----|----|----|----|---|----|----|----|
| | 61 | 53 | 49 | 8 | 71 | 1 | 18 | 11 | 57 |

Table 3. The Delay Coefficient of Test Sample 1 at n=1

| h_l | real | 3.36 | -0.81 | -0.72 | -0.63 | 0.40 | 0.39 | 0.44 | -0.37 | -0.32 |
|-------|----------------|-------|-------|-------|-------|-------|-------|------|-------|-------|
| | imagi- nary | 3.26 | -0.30 | -0.16 | -0.12 | 0.36 | 0.32 | 0.00 | 0.00 | 0.07 |
| | real | -0.25 | -0.23 | 0.28 | -0.23 | -0.02 | -0.17 | 0.13 | 0.17 | 0.17 |
| | imagi- nary | 0.20 | -0.21 | 0.00 | -0.10 | 0.23 | -0.15 | 0.17 | 0.11 | 0.12 |

Continue the characteristics calculation (fingerprint) to get all the characteristics of the test samples, using the established classification model to get classification result, the data of test sample 1 belong to scene 1, the data of test sample 2 belong to scene 2, which are consistent with actual measurement results, it shows that the established feature extraction model in this paper is effective. Test results are shown in Table 3.

Table 3. Characteristics of Test Data

| Sample No | Ми | Sig | rf_1 | rf_2 | if_1 | if_2 | p_1 | p_2 | S_r | scene |
|--------------|------|------|--------|--------|--------|--------|-------|-------|-------|-------|
| Test1 | 8.65 | 1.02 | 271.25 | 479.25 | 271.25 | 479.25 | 2.93 | 25.93 | 1.70 | 1 |
| Test2 | 8.17 | 1.08 | 15.75 | 734.75 | 15.75 | 734.75 | 0.07 | 20.03 | 1.26 | 2 |

5. Conclusion

This paper describes an inversion based on compression and channel observation and a feature extraction model of wireless channel based on local weighted average of *K*-nearest neighbor classification model. The experimental results show that the model has the characteristics of high recognition rate and good applicability in different scenarios or different geographical position. This model solved the channel choice problem of the wireless signal transmission, filled the blank of feature extraction of wireless channel in the complex environment of the communications industry to a certain extent, has larger application space in the wireless signal optimization, the network base station location and complex environment signal distinction.

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