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Multi-Scene Doppler Power Spectrum Modeling of LEO Satellite Channel Based on Atlas Fingerprint Method

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ABSTRACT The modeling of low earth orbit (LEO) satellite channel depends on its Doppler power spectrum. Due to satellite during transit, diversity and dynamic channel scene, the modeling of Doppler power spectrum has two serious problems: one is that the shape of the Doppler power spectrum will vary with the change of scenes and time, but the use of the existing traditional Doppler power spectrum models is difficult to accurately describe them. The other one is that the amount of measured data used for modeling is too large to handle, and data aliasing is easy to occur between different scenes, which will make it difficult to ensure the accuracy of model parameter fitting. In this paper, a two-side truncated asymmetric Doppler power spectrum model is proposed to universally describe the Doppler power spectrum during satellite transit. In addition, the atlas fingerprint method clustering is adopted to realize the classification of the measured data samples of Doppler power spectrum in multiple scenes, and the data with the strongest representation ability in each scene is selected to fit the model parameters. The simulation results show that the proposed model is in good agreement with the measured data. Therefore, parameter fitting using the proposed method can improve the accuracy of the model, so as to better describe the characteristics of LEO satellite channel fading in the frequency domain.

INDEX TERMS LEO satellite channel, Doppler power spectrum model, multiple scenes, atlas fingerprint, parameter fitting.

I. INTRODUCTION

In recent years, LEO satellite constellation network has become the focus of much attention. It can simultaneously meet the requirements of small transmission delay, low transmission loss, high transmission rate and global coverage [1], [2]. Due to these advantages, a variety of services can be provided, including but not limited to global mobile broadband communications, aviation and navigation surveillance, spectrum monitoring, navigation enhancement, Internet of Things, airborne broadband, etc. [3]. In the past two decades, the market of LEO satellites has grown significantly and will expand rapidly in the next few years [4].

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From 2016 to 2025, the average number of small satellite launches is expected to be in the four digits [5]. Several companies have announced plans to launch thousands of LEO satellites around 2022 [6], [7], including SpaceX, OneWeb, Kepler and SPUTNIX. Such a hot deployment of satellite communication has also become an indispensable means to achieve a space-air-ground-sea integrated communication network [8]. Additionaly, in the latest research on Non-Terrestrial Networks (NTN) released by the 3rd Generation Partnership Project (3GPP) recently, [9]–[11] mainly discussed the deployment scheme of LEO satellite system, the definition of system and architecture parameters, and the adaptability of the new radio technology. Among them, LEO satellite channel model is regarded as an important part, because it is the premise for the design and evaluation of its communication system. Therefore, how to accurately model the channel characteristics of LEO satellite is a fundamental problem that needs to be solved urgently in the current standardization process.

In general, channel modeling mainly relies on fading distribution, Power delay profile (PDP), Doppler power spectrum and other statistical properties. Among them, the Doppler power spectrum can reflect the Doppler effect in the channel, which is caused by the Doppler frequency shift of multipath. In LEO satellite channel, the high-speed movement of the satellite (with a speed of 5 to 10 km/s) will lead to a great Doppler shift and Doppler shift change rate [12]. Such a large Doppler shift will seriously degrade the performance of high-throughput systems, such as OFDM systems which are sensitive to frequency offset [13], [14]. In addition, during the transit of LEO satellite, the communication elevation and scene will change continuously, and the multipath effect near the receiver will also change dynamically, which will deeply affect the Doppler power spectrum. Therefore, we establish a Doppler power spectrum model to describe the Doppler effect of the channel, which is the premise of designing the key technology to overcome its influence. In fact, many existing researches have applied the PDP of LEO channel to channel modeling, but less attention has been paid to the Doppler power spectrum [15], and the traditional Doppler power spectrum models of terrestrial mobile channel are still used, such as Jakes, Flat, Rician, Gaussian, etc. However, different from the terrestrial mobile communication channel, the characteristics of LEO satellite channel are mainly reflected in three aspects:

1) In the receiving environment, there are usually fewer obstacles and low scattering degree, and there is an obvious line of sight (LOS) component accompanied by a small number of multipath components;

2) The high-speed relative motion of low-orbit satellites to the earth causes large Doppler frequency offset and frequency offset rate;

3) During satellite transit, regular changes in communication elevation angle will lead to changes in the time evolution process of channel heterogeneous fading, including large-scale fading and small-scale fading.

These unique characteristics make the LEO satellite channel doppler power spectrum show some new dynamic shapes, which are significantly different from the existing ground mobile channel doppler power spectrum. Traditional doppler power spectrum models are no longer applicable to the description of LEO satellite channel characteristics due to their problems such as single scene orientation, insufficient dynamic representation ability and low accuracy. Therefore, a more appropriate modeling method is needed to improve the accuracy and applicability of the multi-scene power spectrum model, which becomes the motivation of the research work in this paper.

The Doppler power spectrum model can usually be established by the following steps: First, a geometric model of signal propagation is constructed according to the scattering characteristics in a specific scene. Then, the received signal is represented mathematically and its autocorrelation function is obtained. Finally, according to The Wiener-Khinchin theorem, the Fourier transform of autocorrelation function is obtained to obtain the Doppler power spectrum. Clarke first proposed the well-known Jakes power spectrum [16]. Under the condition of Rayleigh fading, it is assumed that AoA of the incident wave is uniformly distributed on the azimuth plane $[0, 2\pi]$. Under the action of doppler expansion, the doppler power spectrum presents a symmetrical shape of "U" shape. This model has been widely used in many existing channel models such as COST-207 [17], WINNER II [18], ITU-R channel model [19], 3GPP NR channel model [20] and so on. Subsequently, Aulin expanded the model in [21] to three dimensions (3D), taking into account the distribution of multiple paths on the elevation plane in addition, thus improving the accuracy of the model. However, both the models [16] and [21] assume that the received multipath signals are distributed on the azimuth surface, which is too idealized and only supports the scene with complex receiving environment and rich multipath. However, in the environment with fewer scatterers or uneven distribution, the applicability of this model will be greatly reduced [22]. Patzold *et al.* [23] pointed out that in practice, due to the shielding and absorption of the signal by the scatterer and the sparsity of the multipath, the arrival Angle distribution of the multipath signal at the receiving end would be changed, resulting in the limitation of the asymmetry and width extension of the Shape of the Doppler power spectrum. Based on this conclusion, Jakes power spectrum of double-ended truncation is proposed, and the model is further close to the real channel situation. In addition, In their research, Kasparis *et al.* [24] analyzed the influence of antenna directivity and beam width on The Doppler power spectrum in view of the fact that the receiving antenna of the commercial satellite terminal is usually pointing antenna, and proposed the Laplace Doppler power spectrum model for the signal reception of pointing antenna. According to the above theoretical model, the Doppler power spectrum is not only determined by the Doppler frequency offset, but also determined by the Angle distribution of the incident wave, the degree of multipath fading and the directivity of the receiving antenna. After the model is established, it is usually necessary to use the measured data to fit the model parameters, so that the established model is closer to the measured data, that is, the description of the real channel is more accurate. Ha *et al.* [25] adopted Lp-Norm algorithm to perform the steps of multi-scene measured data fitting of doppler power spectrum model parameters, and obtained the parameter sets of the model in each scene. Rougerie *et al.* [26] adopted a fitting method of weighted minimum mean square error for land mobile satellite (LMS) channel transmission environment to provide the optimal trade-off between Doppler spectrum shape and coherence time. However, the above two parameter fitting methods both consider the average Doppler power spectrum of stationary channels under fixed scenes, and do not analyze the instantaneous Doppler power spectrum of non-stationary channels such as LEO satellites. In addition, due to the continuous change of elevation angle and receiving environment, the Doppler power spectrum also has fast time variation, which results in too large difference between the measured data samples to directly apply the above fitting methods.

To sum up, the existing Doppler power spectrum modeling methods have the following two problems:

1) The traditional Doppler power spectrum model is relatively single with insufficient characterization ability, which cannot fully describe the diversified Doppler power spectrum in LEO satellite channel under multiple scenes;

2) Due to the large amount of measured data used for modeling, it is difficult to accurately obtain the parameters of the Doppler power spectrum model in each scene, resulting in the low accuracy of the established model.

To solve the above problems, first of all, based on the existing traditional model, a slightly modified Doppler power spectrum model is proposed, which is suitable for LEO satellite channel. Then, the shape of the Doppler power spectrum also changes due to the different channel fading in different scenes. Therefore, an atlas fingerprint method of Doppler power spectrum modeling is adopted in this paper that that the study of channel characteristics are transformed into the study of graphical shape characteristics. This method can be viewed as the model parameter fitting before data preprocessing method: Firstly, based on the measured data extraction to the geometrical characteristics of the doppler power spectrum graph to build atlas fingerprint. Then the fingerprint clustering process to select the best reference fingerprint samples, subsequently select the scene to the Doppler power spectrum characterization ability strongest data fitting model parameters. Finally, a more accurate Doppler power spectrum model is obtained. The advantage of this method is that it is easy to process and analyze large measurement samples in multiple scenes, and it can effectively reduce the parameter fitting error of LEO satellite Doppler power spectrum model caused by rapid changes of multiple scenes in the LEO satellite channel, so as to improve the accuracy of the model.

The rest of this article is organized as follows. In section II, combined with the characteristics of LEO satellite channel and on the basis of the traditional Jakes spectrum, the improved Doppler power spectrum model is proposed. In section III, a model parameter fitting method based on fingerprint clustering is proposed and the implementation steps are given. In section IV, a simulation environment is built to verify the superiority of the proposed method. Finally, section V summarizes the whole paper and looks forward to the application of this method in channel modeling.

II. PROPOSED DOPPLER POWER SPECTRUM MODEL

In this section, combined with the characteristics of LEO satellite channel, a geometric model for analyzing signal propagation is established, and the general Doppler power spectrum expression is overturned. Based on the traditional model, the improved model is proposed.

A. SIGNAL PROPAGATION MODEL

The research scene of this paper is a single low orbit satellite communication to earth. The orbital altitude is usually between 500 km and 1500 km. The frequency band used is Ku/Ka band, and the Doppler frequency offset will be large. At the same time, in order to fully study the characteristics of Doppler power spectrum, we make the following reasonable assumptions:

1) Assume that the receiving antenna used by the ground receiver is an isotropic omnidirectional antenna, which can fully receive multipath signals from all directions;

2) It is assumed that the multipath effect is only caused by the refraction of randomly distributed scatterers near the ground mobile terminal [27].

3) In this frequency band, the multi-path propagation signal only needs to consider the result of one bounce caused by nearby scatterer, while the signal scattering caused by distant scatterer and the received power of the signal after multiple bounce can be ignored [28].

A general signal propagation model based on 3D coordinate system is constructed in the LEO satellite communication scene, as shown in Fig. 1.

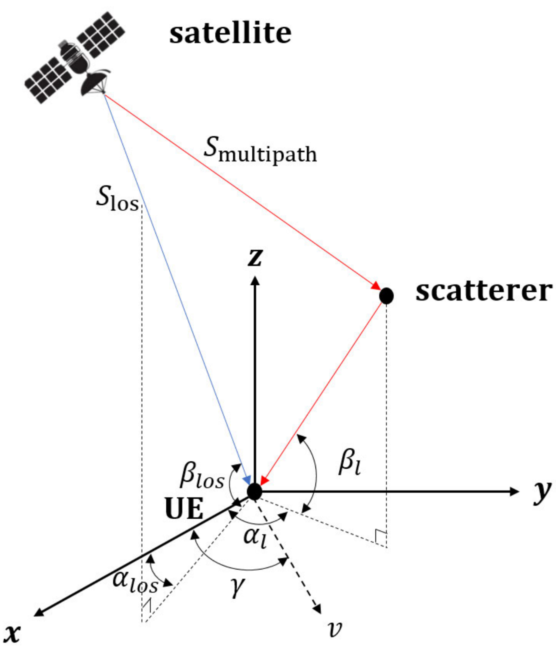

FIGURE 1. Geometric model of signal propagation.

In the LEO satellite communication channel, the transmitted signal is composed of a dominant LOS path and N multipaths attached around it. At time t, the total received signal can be expressed as

$$s(t) = s_{LOS}(t) + s_{NLOS}(t) = h_{LOS}(t)x(t) + \sum_{l=1}^{N} h_l(t)x(t) \tag{1}$$

where, $s_{LOS}(t)$, and $s_{NLOS}(t)$ are LOS component and multipath component respectively. $x(t)$ is transmission signal with a power value of 1. $h_{LOS}(t)$ and $h_l(t)$ are the channel impulse response of LOS component and the lth multipath respectively, and N and N is the number of multipath.

The channel impulse response of LOS component can be expressed as

$$h_{LOS}(t) = \sqrt{P_0(t)} \cdot e^{j2\pi f_d(t) \cdot t} \tag{2}$$

where, p_0 is the gain coefficient of LOS component. $f_d(t)$ is Doppler shift, caused by the high speed relative motion of the satellite towards the ground, which can be easily calculated based on the position information between the satellite and the ground [29].

The channel impulse response of the multipath component can be expressed as

$$h_l(t) = \sqrt{P_l(t)} \cdot e^{(-j2\pi f_{d_l}(t) \cdot t + \phi_l^0)} \tag{3}$$

where, P_l, ϕ_l^0, and f_{d_l} respectively represent the gain coefficient, initial phase and Doppler frequency offset of the lth multipath signal. $P_1(t) = \sum_{l=1}^{N} p_l(t)$, $P_1(t)$ follows Rayleigh distribution. ϕ_l^0 follows Uniform distribution on $[0, 2\pi]$. f_{d_l} can be represented as

$$f_{d_l}(t) = f_d(t) \cdot \cos(\alpha_l - \gamma) \cdot \cos \beta_l \tag{4}$$

where, α_l and β_l are the angle of arrival (AoA) of azimuth and elevation plane of the lth multipath signal reaching the receiver respectively, and γ is the angle between the motion direction of the ground moving receiver and the X-axis.

For the multipath component, the autocorrelation function at time t and $t + \tau$ is calculated as follows:

$$\begin{aligned} R(\tau) &= R(t, t+\tau) = \left\langle h_l(t) \cdot h_l^*(t+\tau) \right\rangle_t \\ &= \sum\nolimits_{l,m}^{N} \left\langle \sqrt{P_l(t) P_m(t)} \right\rangle_{\alpha,\beta} \\ &\quad \cdot \left\langle e^{-j2\pi f_{d_l}(t) \cdot t} \cdot e^{-j2\pi f_{d_l}(t) \cdot (t+\tau)} \right\rangle_{\alpha,\beta} \cdot \left\langle e^{-j(\phi_l^0 - \phi_m^0)} \right\rangle_{\varphi} \end{aligned} \tag{5}$$

$\langle \cdot \rangle$ represents calculating expectation. When N is large enough, the above equation can be further expressed as

$$\begin{aligned} R(\tau) &= \sum_{l=1}^{N} \langle P_l \rangle_{\alpha,\beta} \cdot \left\langle e^{-j2\pi f_{d_l}(\tau) \cdot \tau} \right\rangle_{\alpha,\beta} \\ &= P_1 \int_{\alpha} \int_{\beta} G_\alpha(\alpha) G_\beta(\beta) \cdot P_\alpha(\alpha) P_\beta(\beta) \\ &\quad \cdot e^{-j2\pi f_{d_l}(\tau) \cdot \tau} \cdot d\alpha d\beta \end{aligned} \tag{6}$$

where, $G_\alpha(\alpha)$ and $G_\beta(\beta)$ represent the angular gain at azimuth and altitude of the omni-directional antenna receiving the signal, respectively. We assume that $G_\alpha(\alpha) = G_\beta(\beta) = 1$. $P_\alpha(\alpha)$ and $P_\beta(\beta)$ represents the AoA distribution of azimuth plane and altitude plane, respectively. When considering the two-dimensional case only, assume that $P_\alpha(\alpha)$ is uniformly distributed on $[0, 2\pi]$, i.e

$$P_\alpha(\alpha) = \begin{cases} \dfrac{1}{2\pi}, & 0 \leq \alpha \leq 2\pi \\ 0, & elsewhere \end{cases} \tag{7}$$

Substitute $P_\alpha(\alpha)$ into (6) and get the autocorrelation function

$$R(\tau) = P_1 \cdot I_0(2\pi f_{d_{max}} \cdot \tau) \tag{8}$$

where, $I_0(\cdot)$ is the first kind of zero order Bessel function, and $f_{d_{max}}$ is the maximum Doppler shift. By taking the Fourier transform of (8), we can obtain the Doppler power spectrum of the multipath component

$$S_{NLOS}(f) = \frac{P_1}{2\pi f_{d_{max}} \sqrt{1 - \left(\frac{f}{f_{d_{max}}} \right)^2}} \tag{9}$$

At this time, (10) is Jakes spectrum.

For the LOS component, the Doppler power spectrum $S_{LOS}(f)$ is a discrete value in frequency domain.

$$S_{LOS}(f) = P_0 \cdot \delta(f - f_d) \tag{10}$$

where $\delta(\cdot)$ is Dirichlet function.

Combined with equation (9) and (10), the Doppler power spectrum of LEO satellite can be expressed as

$$\begin{aligned} S(f) &= S_{LOS}(f) + S_{NLOS}(f) \\ &= P_0 \cdot \delta(f - f_d) + \frac{P_1}{2\pi f_{d_{max}} \sqrt{1 - \left(\frac{f}{f_{d_{max}}} \right)^2}} \end{aligned} \tag{11}$$

The schematic diagram of Doppler power spectrum of LEO satellite channel is shown in Fig. 2. f_c is carrier frequency, and f_d is Doppler frequency shift caused by satellite movement. The multipath effect is only caused by the scattering of the environment near the ground receiver. Due to different angles of multi-path signals arriving at the receiving end, they have different Doppler frequency shifts, resulting in U-shaped spread of doppler power spectrum. The spread value of f_{max} is related to the scattering intensity of the ground receiving environment. The discrete peak represents the LOS path, whose abscission position is off-center to $f_{d_{los}}$ due to Doppler shift caused by the movement of the receiver. If the receiver is static, $f_{d_{los}}$ will be at the center of the spectrum. For simplicity, the receiver is assumed to be static in this paper.

B. THE PROPOSED IMPROVED MODEL

Due to the motion of LEO satellite, the fading characteristics of the channel will change with the change of communication elevation angle, while the traditional Doppler power spectrum model is difficult to fully describe the diversified fading characteristics. Therefore, we improve the model based on the classical Jakes spectrum, so as to propose a Doppler power spectrum model suitable for LEO satellite channel scene.

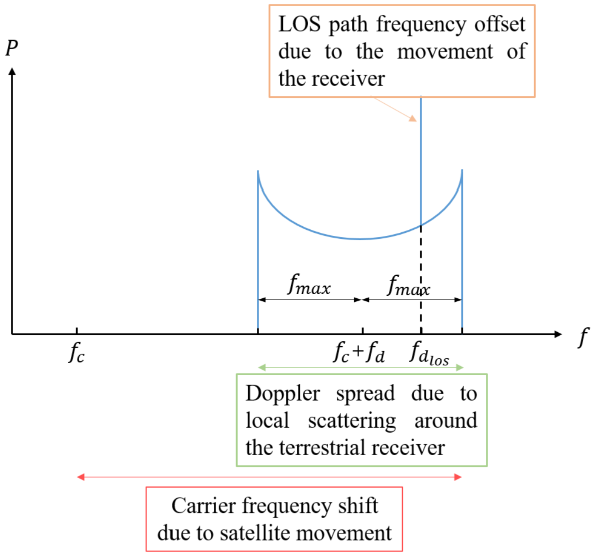

FIGURE 2. **Schematic diagram of Doppler power spectrum of LEO satellite channel.**

An example is given to illustrate that when the communication elevation angle is low, the channel has the following characteristics:

1) The distance between the satellite and the ground receiving end is relatively far, and it is easy to be blocked by taller objects such as tall buildings and trees, so the probability of shadow fading is higher and the path loss is higher.

2) The transmitted signals at low elevation angle are more likely to be scattered by obstacles in the receiving environment, so the multipath effect is stronger.

3) The relative motion speed between the satellite and the ground receiver is large, so the doppler frequency shift of the transmitted signal is also large.

With the continuous movement of the satellite, the decline will be reduced in the transition to the high elevation region. The Doppler power spectrum in different scenes of LEO satellite channel is shown in Fig. 3. θ_1, θ_2 and θ_3 are three different communication elevation angles at different moments during the transit of the satellite. It can be seen that the shape of the Doppler power spectrum will change with the change of elevation angle. According to the above analysis, the original assumption of Jakes power spectrum is not suitable for LEO satellite channels, or it can only be considered as a special case at a certain time. Therefore, we propose a two-side truncated asymmetric Doppler power spectrum model.

$$S(f) = \begin{cases} 2[1 + sgn(f + f_{dev}) \cdot \sin\alpha] & \\ \quad \cdot S_{NLOS}(f) + S_{LOS}(f), & |f| \leq k \cdot f_{d_{max}} \\ 0, & elsewhere \end{cases} \tag{12}$$

where, $S_{LOS}(f)$, as shown in (10), different from the traditional two-sided truncated Doppler power spectrum, it specially describes the effect of LOS component on Doppler power spectrum. $S_{NLOS}(f)$ is approximate to (9), but its maximum Doppler frequency shift is limited by k, $0 \leq k \leq 1$.

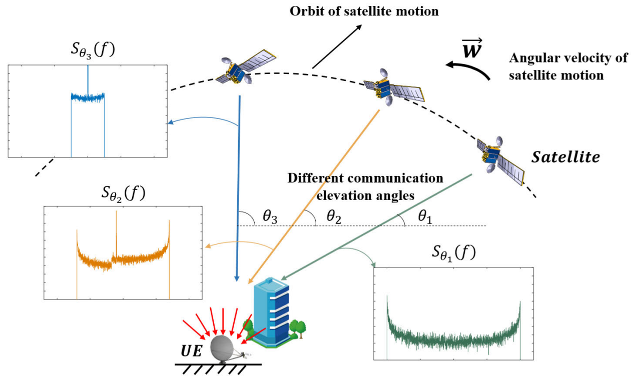

FIGURE 3. **Doppler power spectrum pattern of LEO satellite channel in different scenes.**

Two-side truncation is used to describe the limitation of doppler power spectrum broadening and asymmetry caused by the small number of multipath signals and shadow fading resulting in the arrival Angle distribution of multipath signals at the receiving end not satisfying the uniform distribution on $[0, 2\pi]$ [30]. $sgn(\cdot)$ represents the symbolic function. $f_{d_{max}}$ is the maximum value of Doppler shift. f_{dev} is the frequency offset adjustment factor, $-1 \leq f_{dev} \leq 1$, and α is the correlation factor, $-\frac{\pi}{2} \leq \alpha \leq -\frac{\pi}{2}$. They control the position and size of the asymmetry of Doppler power spectrum respectively. Only the shape of the Doppler power spectrum is considered, and the shift of the doppler spectrum caused by the satellite motion is not taken into account. The doppler power spectrum obtained is shown in Fig. 4.

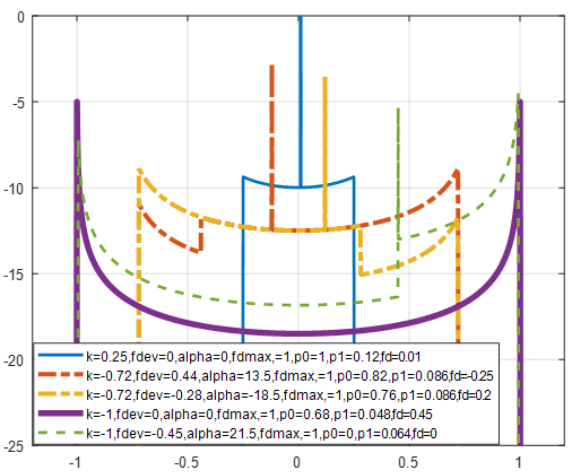

FIGURE 4. **Proposed improved LEO satellite Doppler power spectrum model.**

The above model can comprehensively describe the diversified Doppler power spectrum in LEO satellite channel scenes, because we can determine a set of specific parameter sets in the Doppler power spectrum model $\{f_{dev}, \alpha, k, f_{d_{max}}, P_0, P_1, f_d\}$ for different scenes to obtain the Doppler power spectrum model in different scenes. This step needs to be completed by means of data preprocessing and

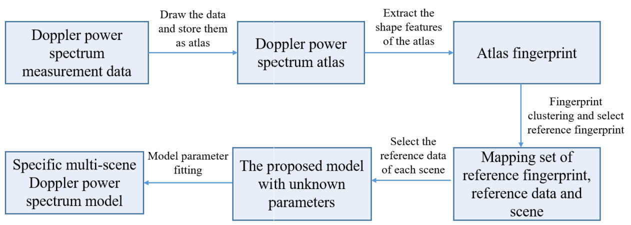

FIGURE 5. Block diagram of Doppler power spectrum modeling process of LEO satellite with multiple scenes.

parameter fitting combined with the measured data, and the specific process is described in III.

III. DOPPLER POWER SPECTRUM MODELING BASED ON ATLAS FINGERPRINT METHOD

In this section, we propose a novel method of model parameter fitting and introduce its implementation steps. The proposed Doppler power spectrum model contains a set of unknown parameters, which need to be obtained by fitting the model with measured data. Due to the motion of LEO satellites, the communication elevation angle will change regularly. The decaying conditions at different elevation angles are different, and the ground terminal may experience different environments. Therefore, during the transit of LEO satellite, its communication channel will experience dynamic changes of various scenes. Each set of parameter values in the proposed model correspond to the Doppler power spectrum in a scene. In order to accurately fit the model parameters, this section introduces a model parameter fitting method based on fingerprint. The flow diagram of the proposed modeling method is shown in Fig. 5, and its steps are summarized as follows:

1) To obtain the doppler power spectrum measurement data of large sample size, we draw each group of data and store them in the form of a graph;

2) Extract the shape features of each graph as a corresponding fingerprint to establish a fingerprint database;

3) Fingerprint clustering was used to classify multiple scenes and establish mapping relationship between reference data and scenes;

4) Select the reference data corresponding to the feature vectors with the strongest representation ability in each category to fit the model parameters, so as to obtain the specific Doppler power spectrum model in each scene.

A. ACQUISITION OF MEASURED DATA

In order to achieve the parameter fitting of the multi-scene Doppler power spectrum model, it is necessary to obtain the measured data in the multi-scene first and extract the Doppler power spectrum from the measured time-domain signals. The measurement method can be referred to [31], and the commonly used detection signals are single frequency sinusoidal wave or m sequence. In this paper, the measurement data acquisition method is as follows: first, select a specific receiving environment (such as rural, suburban, urban, etc.). Then, the single frequency sinusoidal wave is used as the transmission signal, which is continuously transmitted by the satellite transponder throughout the transit period. The ground receiver uses an omni-directional antenna to receive the RF (radio frequency) signal transmitted by satellite. The received RF signal data is observed and stored in real time by connecting the spectrum analyzer. Finally, the data is imported to the PC for processing, and the Doppler power spectrum data of the signal is calculated for our modeling.

Assume that the doppler power spectrum data obtained by measurement is denoted as $S_{exp}(f, t_n)$, Where, t_n is the central moment of the nth Doppler power spectrum snapshot, $n = 1, 2, \ldots, N$, N is the number of Doppler power spectrum snapshots, which is also the size of data samples. The duration of each snapshot is $\Delta\tau$. To ensure the accuracy of measurement data, $\Delta\tau$ should not be greater than the quasi-stationary time of the channel.

Next, we need to consider how to distinguish multiple scenes from massive measurement data, and select the data with the strongest characterization ability in each scene to fit the parameters of the Doppler power spectrum model under the corresponding scene.

B. ATLAS FINGERPRINT STRUCTURE

The shape of Doppler power spectral is an important basis of modeling, which can reflect the doppler and multipath fading channel and other information. Therefore, from the perspective of shape characteristics of Doppler power spectrum, we draw the measured data and extract its shape characteristics to construct the atlas fingerprint and establish the fingerprint database. This processing facilitates scenes classification. It is worth mentioning that the geometric statistical features of the extracted atlas are corresponding to the channel characteristics, and more importantly, the method can make use of a small number of graphic features to represent the channel characteristics more comprehensively, as shown in the Fig. 6. As the atlas is a fast fluctuation curve, the fingerprint constructed by us can be composed of a set of vectors aiming at geometric features of the curve, including mean width, mean height, peak value, kurtosis, skewness, etc. The fingerprint vector of $S_{exp}(f, t_n)$ is expressed as follows:

$$\boldsymbol{x_n} = \left[\mu_{width_n}, \mu_{hight_n}, H_{\max_n}, K_n, S_n\right]_{1\times 5} \tag{13}$$

The established fingerprint database can be represented as

$$\boldsymbol{X} = \left[\boldsymbol{\mu}^{T}_{\boldsymbol{width}}, \boldsymbol{\mu}^{T}_{\boldsymbol{hight}}, \boldsymbol{H}^{T}_{\boldsymbol{max}}, \boldsymbol{K}^{T}, \boldsymbol{S}^{T}\right]_{N\times 5} \tag{14}$$

where, $\boldsymbol{\mu_{width}} = [\mu_{width_1}, \mu_{width_2}, \ldots, \mu_{width_N}]$, $\boldsymbol{\mu_{height}} = [\mu_{height_1}, \mu_{height_2}, \ldots, \mu_{height_N}]$, $\boldsymbol{H_{max}} = [H_{max_1}, H_{max_2}, \ldots, H_{max_N}]$, $\boldsymbol{K} = [k_1, k_1, \ldots, k_N]$, $\boldsymbol{S} = [s_1, s_1, \ldots, s_N]$.

The mean width of the spectrum shape can describe the Doppler spread of the Doppler power spectrum in the channel, which can reflect the richness of multipath and the relative velocity between the transceivers. The calculation

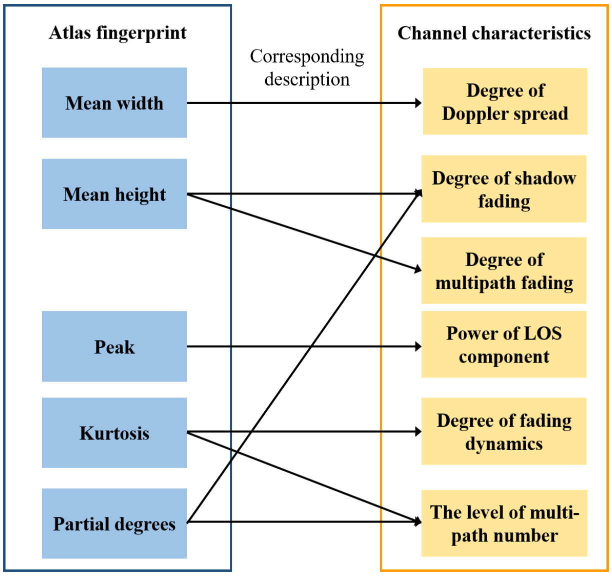

FIGURE 6. Corresponding description relationship between fingerprint and channel characteristics.

formula is as follows:

$$\mu_{width} = \frac{x_{max} - x_{min}}{2} \tag{15}$$

where, x_{max} and x_{min} are the maximum and minimum values of the horizontal coordinates of the atlas shape respectively.

The mean height of spectrum shape can describe the average multipath fading of channel, and it can reflect the degree of signal affected by shadow fading and multipath fading. The calculation formula is as follows:

$$\mu_{height} = \frac{\sum_{n=1}^{N} y_n}{N} \tag{16}$$

where, y_n is the value of the ordinate of the atlas shape.

The position of the highest point of the spectrum shape generally represents the information of the LOS path, and its peak value H_{max} represents the power of LOS path, which is related to the distance from the satellite to the ground and the shadow fading caused by the occlusion in the receiving environment. Its horizontal position represents the Doppler frequency shift of LOS path caused by the mobility of receiver.

Kurtosis K is the statistic of the steepness or smoothness of the spectrum shape, which can describe the fading dynamic degree and fading depth of the channel. When the curve is steeper and the rising and falling ground is more intense, the more dynamic and deep the multipath fading is. The calculation formula is as follows:

$$K = \frac{\sum_{n=1}^{N} (y_n - \mu_{height})^4}{n\sigma^4} - 3 \tag{17}$$

where, σ is the standard deviation.

The skewness S of the spectrum shape is a measure of the degree of symmetry of the curve. Due to the small number of multipaths in the channel or the shadow fading caused by the uneven distribution of occlusion, the shape of Doppler power spectrum will appear different degrees of asymmetry. The calculation formula is as follows:

$$S = \frac{\sum_{n=1}^{N} (y_n - \mu_{height})^3}{n\sigma^3} \tag{18}$$

After feature extraction, the mapping relationship between each fingerprint and the measured Doppler power spectrum data corresponding to the fingerprint is established, i.e. there is a mapping relationship between the fingerprint sample $\boldsymbol{x_n}$ and the measurement data sample $S_{exp}(f, t_n)$.

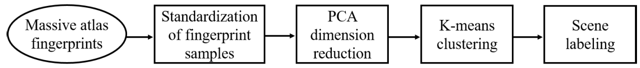

FIGURE 7. Process of fingerprint clustering.

C. ATLAS FINGERPRINT CLUSTERING

Aiming at the atlas fingerprint samples of the above large data volume, K-means clustering processing based on the minimum Euclide distance is adopted to realize the classification of multi-scene LEO satellite channels. This process includes fingerprint standardization, PCA dimensionality reduction, K-means clustering, and scene labeling, as shown in Fig. 7.

1) Standardization of fingerprint samples

First of all, we adopted the deviation standardization method to conduct dimensionless processing of fingerprints, and eliminated the influence of too large or too small value, so that the range of each characteristic value in all fingerprints was between [0, 1], so as to facilitate the subsequent PCA reduction and clustering processing. The $\boldsymbol{\mu_{width}}$ can be denoted by normalization of each column in fingerprint database $\boldsymbol{X}$ (i.e. the value of each type of feature)

$$\overline{\mu}_{width_n} = \frac{\mu_{width_n} - Min\{\boldsymbol{\mu_{width}}\}}{Max\{\boldsymbol{\mu_{width}}\} - Min\{\boldsymbol{\mu_{width}}\}}, \quad n = 1, 2, \ldots, N \tag{19}$$

where, $Max\{\cdot\}$ and $Min\{\cdot\}$ are maximum and minimum functions.

Similarly, it is easy to standardize $\boldsymbol{\mu_{hight}}, \boldsymbol{H}_{\mathbf{max}}, \boldsymbol{K}, \boldsymbol{S}$, and the fingerprint library $\overline{\boldsymbol{X}}$ is obtained.

$$\overline{\boldsymbol{X}} = Dst(\boldsymbol{X}) = \left[\overline{\boldsymbol{\mu}}^{\boldsymbol{T}}_{\boldsymbol{width}}, \overline{\boldsymbol{\mu}}^{\boldsymbol{T}}_{\boldsymbol{hight}}, \overline{\boldsymbol{H}}^{\boldsymbol{T}}_{\mathbf{max}}, \overline{\boldsymbol{K}}^{T}, \overline{\boldsymbol{S}}^{T}\right]_{N\times 5}$$

$Dst(\cdot)$ is called a deviation normalized function.

Then, due to the dynamics and diversity of signal transmission scenes, fingerprint samples from different scenes will appear similar or aliasing, which will seriously affect the convergence speed and accuracy of subsequent clustering processing. Therefore, after a square operation on $\overline{\boldsymbol{X}}$, another deviation normalization was performed to increase the degree of differentiation among the fingerprint samples.

$$\overline{\overline{\boldsymbol{X}}} = Dst\left(\overline{\boldsymbol{X}}\right) = \left[\overline{\overline{\boldsymbol{\mu}}}^{\boldsymbol{T}}_{\boldsymbol{width}}, \overline{\overline{\boldsymbol{\mu}}}^{\boldsymbol{T}}_{\boldsymbol{hight}}, \overline{\overline{\boldsymbol{H}}}^{\boldsymbol{T}}_{\mathbf{max}}, \overline{\overline{\boldsymbol{K}}}^{T}, \overline{\overline{\boldsymbol{S}}}^{T}\right]_{N\times 5}$$

2) PCA dimension reduction

PCA method is adopted to reduce the dimension of high-dimensional fingerprints to two dimensions, and the similarity between fingerprint samples can be evaluated by Euclidean distance, which provided convenience for subsequent clustering processing in two-dimensional plane. The fingerprint database after dimension reduction is recorded as

$$\widetilde{X} = PCA\left(\overline{\overline{X}}\right) = \left[v_1^T, v_2^T\right]_{N\times 2} \tag{20}$$

where, $\boldsymbol{v_1} = [v_{11}, v_{12}, \ldots, v_{1N}]$, $\boldsymbol{v_2} = [v_{21}, v_{22}, \ldots, v_{2N}]$, the nth fingerprint sample after dimension reduction is recorded as $\widetilde{\boldsymbol{x}}_{\boldsymbol{n}} = [v_{1n}, v_{2n}]$.

3) K-means clustering based on minimum European distance

By clustering the fingerprints, the detailed classification of multiple scenes of the measured data was realized. Through two-dimensional visual analysis, the best reference data could be selected later to correctly fit the model parameters. The clustering method is as follows:

Firstly, the fingerprint is mapped to a two-dimensional plane according to the eigenvalues of two dimensions to form a point set. Then, according to the measurement experience K different scenes, randomly selected from an initial center of mass in each scene as the clustering center, computing each point to the center of the Euclidean distance and divided into K clusters, calculation of each cluster centroid again, then to cluster and update the centroid iteration process, until the center of mass is no longer change. Here, the center of mass of each cluster obtained by recalculation is obtained according to the objective function. The fingerprint data of Euclidean distance is taken into account, and the error sum of squares (SSE) is used as the objective function of clustering. After the cluster is generated by clustering iteration, the smallest sample point of SSE is used as the center of mass of each update:

$$SSE(\boldsymbol{x_n}) = \sum_{i=1}^{K}\sum_{n=1}^{N}(\boldsymbol{c_i} - \boldsymbol{v_n})^2 \tag{21}$$

where, K represents the number of classes, and $\boldsymbol{c_i}$ represents the ith cluster center. Minimizing SSE by solving the ith center $\boldsymbol{c_i}$. The process of minimizing SSE is as follows:

$$\boldsymbol{c_i} = \arg\underset{\boldsymbol{v_n}}{Min}\left\{SSE(\boldsymbol{x_n})\right\} = \underset{\boldsymbol{v_n}}{\arg}\left\{\frac{\partial}{\partial \boldsymbol{v_n}}SSE(\boldsymbol{v_n}) = 0\right\} \tag{22}$$

Thus, we complete the fingerprint clustering. By recording prior information during the previous measurement, each type of fingerprint sample can be labeled so as to realize scene classification.

D. MODEL PARAMETER FITTING

Finally, we use the measured data to fit the doppler power spectrum model parameters of each kind of scene in the LEO satellite channel. Therefore, in order to ensure the accuracy of model parameters, it is very important to select the measured data fitted with parameters in each type of scene. Because

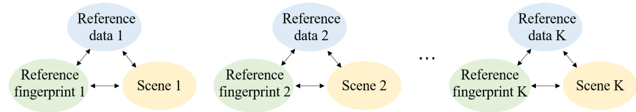

FIGURE 8. Mapping relationship between reference data, reference fingerprint, and scene.

each type of fingerprint sample points near the center of mass of the highest intensity, the doppler power spectrum characteristics of the scene representation ability and generality is the strongest, so we select each type of cluster center of mass of the fingerprint reference fingerprint, the corresponding measured data as case scene doppler power spectrum model reference data. At this point, the mapping relationship among reference data, reference fingerprint and scene is established, as shown in Fig. 8. According to the Doppler power spectrum expression, the parameter set to be fitted contains $\left\{f_{dev}, \alpha, k, f_{d_{max}}, P_0, P_1\right\}$, and the target function can be set using L2-Norm method [26].

$$E_n = [\frac{1}{f_{\max} - f_{\min}} \cdot \int_{f_{\min}}^{f_{\max}} \left|S_{exp}(f, t_n) - S(f_{dev}, \alpha, k, f_{d_{max}}, P_0, P_1)\right|^2 df]^{\frac{1}{2}} \tag{23}$$

When the target function gets the minimum value, the parameter set $\left\{f_{dev}, \alpha, k, f_{d_{max}}, P_0, P_1\right\}$ is obtained. The model in each scene is determined by a unique parameter set. Thus, we have completed the Doppler power spectrum modeling of LEO satellite channel in multi-scene.

E. USAGE OF THE MODEL

In this section, the multi scene Doppler power spectrum modeling based on fingerprint method is completed as above. Here, we also introduce the usage of the proposed model, as shown in the Fig. 9.

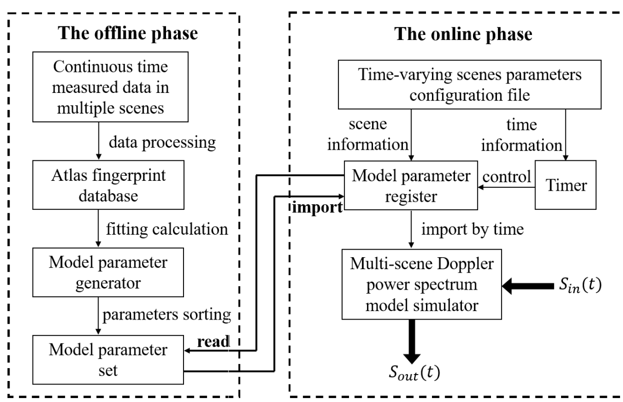

FIGURE 9. The block diagram of the usage of the proposed model.

The model usage consists of offline phase and online phase. In the offline phase, we mainly complete the modeling. Through the actual measurement, the continuous time

Doppler power spectrum measurement data of the satellite in multiple scenarios during the transit period is obtained. By processing the measurement data, the fingerprint database is constructed. The fingerprint clustering method is used to achieve scene classification, and the model parameters are obtained by model fitting for each kind of scene. The obtained parameters are sorted to form a model parameter set. In the online phase, first of all, you need to input the scene configuration file, which contains scene information and time information since the scene will change with time. The scene information is input into the model parameter register, which can read the parameters of the model parameter set in the offline phase according to the scene. The time information is input into the timer, and the model parameter register will import the parameters of each scene into the multi scene Doppler power spectrum model simulator on time according to the control of the timer to generate the model. By importing the input signal into the model simulator, the output signal affected by Doppler effect can be obtained.

IV. SIMULATION AND ANALYSIS

A. DESIGN OF SCENE AND EXPERIMENT

The scenes considered in this experiment are composed of different landforms and elevation angles. The measured data in [9] show the measurement data of Ka band LEO satellite channel. It took into account both suburban and urban receiving environments at 10°, 20°, ..., 80°. Because the measurement results in similar scenes may be little difference, in order to facilitate observation and analysis and explain the conclusion, we select 6 LEO satellite communication scenes composed of suburban and urban receiving environments at three elevation angles of 10°, 40° and 80° to verify the performance of the proposed modeling method. The original Doppler power spectrum data are generated by the improved sum of sinusoids (SOS) simulation method in [30]. At the same time, in order to simulate a large number of continuous time Doppler power spectrum measurement data in each scene, we utilize normal distribution to expand the sample of these 6 typical scenes. Then the graph feature extraction, cluster analysis and model parameter fitting are carried out for these samples. Simulation conditions are shown in the following table:

B. RESULT ANALYSIS

The clustering results of fingerprint samples are shown in the Fig. 10 below: in Fig. 10(a) and Fig. 10(b), before clustering, the divergence degree of fingerprint sample point set varies in different scenes, which is caused by the degree of scattering in the receiving environment. The more complex the receiving environment is, the stronger the scattering degree is and the more scattered the fingerprint samples are. In addition, aliasing occurs among fingerprints of different scene types, which is caused by dynamic changes of Doppler power spectra due to dynamic channel state. Aliasing occurs when the shape characteristics of doppler power spectra are

TABLE 1. Simulation settings.

Parameters		Values		
Altitude		1200km		
Carrier frequency		18.75GHz		
Sampling rate		5M Sample/s		
Receiver mobility		Static		
Doppler power spectrum generation mode		SOS method [30]		
Sample expansion mode		Normal distribution		
Scenes	Environment	Suburban		Urban
	Elevation	10°	40°	80°
Number of samples in each scene		200		
Clustering methods		K-means		
Maximum number of clustering iterations		1000 times		
Parameter fitting method		L2-Norm		

similar. The aliasing of different landforms under the same elevation angle is the most obvious, followed by the aliasing of adjacent elevation angles under the same elevation angle. If we consider more scenes and the size of measurement data or samples is too large, the adverse appearance will be more significant. At this time, it will be difficult to select appropriate data for model parameter fitting. As shown in Fig. 10(c), the fingerprint database is reclassified by clustering iteration based on the minimum Euclide distance. While aliases are eliminated, the reference data for parameter fitting is also selected, that is, the measured data corresponding to each clustering center. This method can be regarded as a preprocessing method of model parameter fitting and an effective guarantee of model accuracy and accuracy.

After the reference data is determined, the L2-Norm method is used to perform model parameter fitting in order to obtain the value of parameter set $\left\{f_{dev}, \alpha, k, f_{d_{\max}}, P_0, P_1\right\}$ when the target function (22) is the smallest. In addition, in order to reflect the superiority of the method proposed in this paper, in this step, we also compare the results of parameter fitting of the mean L2-Norm in [26] and the mean weight minimum mean square error (WMMSE) method in [27], as shown in the Fig. 11.

We evaluated the modeling accuracy by comparing the RMSE between the model curves obtained by different fitting methods and the original data. As can be seen from Fig. 10 and Table 2, the fitting model of Lp-Norm method based on fingerprint clustering proposed in this paper is the most consistent with the measured data, and its performance is better than that of mean Lp-Norm and mean WMMSE method. This is because the Lp-Norm method of fingerprint clustering can overcome the influence of aliasing of data samples in different scenes on parameter fitting. The two methods used for comparison are both fitting based on the average of data samples, which do not deal with the influence of "aliasing phenomenon", but also introduce the fitting error caused by singular data. Therefore, the model error fitted by these two methods is relatively large. In addition, the advantages of the method proposed in this paper will be more significant when more scenes are measured and the amount of measured data is larger. We can divide the scene according to the actual communication scene and the required model

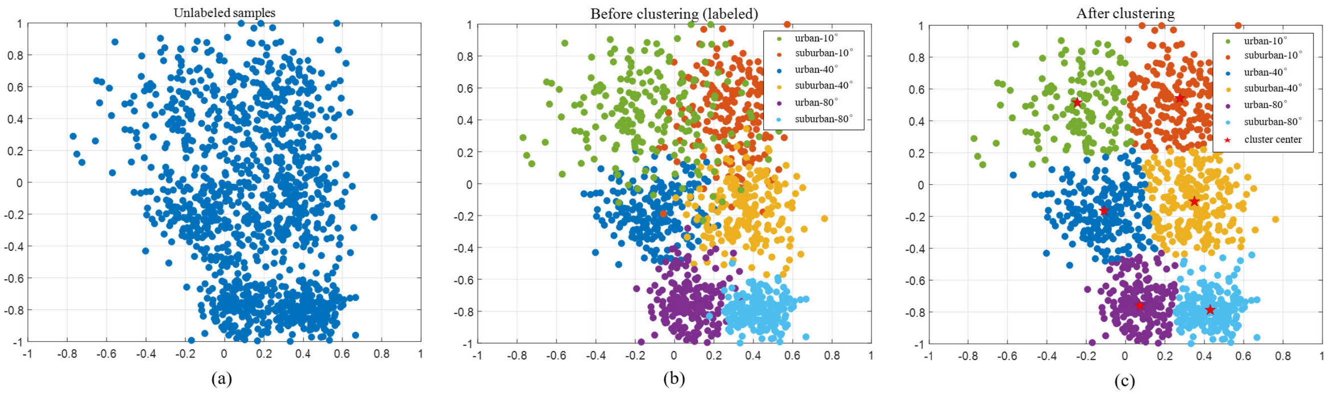

FIGURE 10. Clustering of fingerprint samples in multi-scenes. (a) is the original sample without label.(b) and (c) are the results before and after clustering respectively.

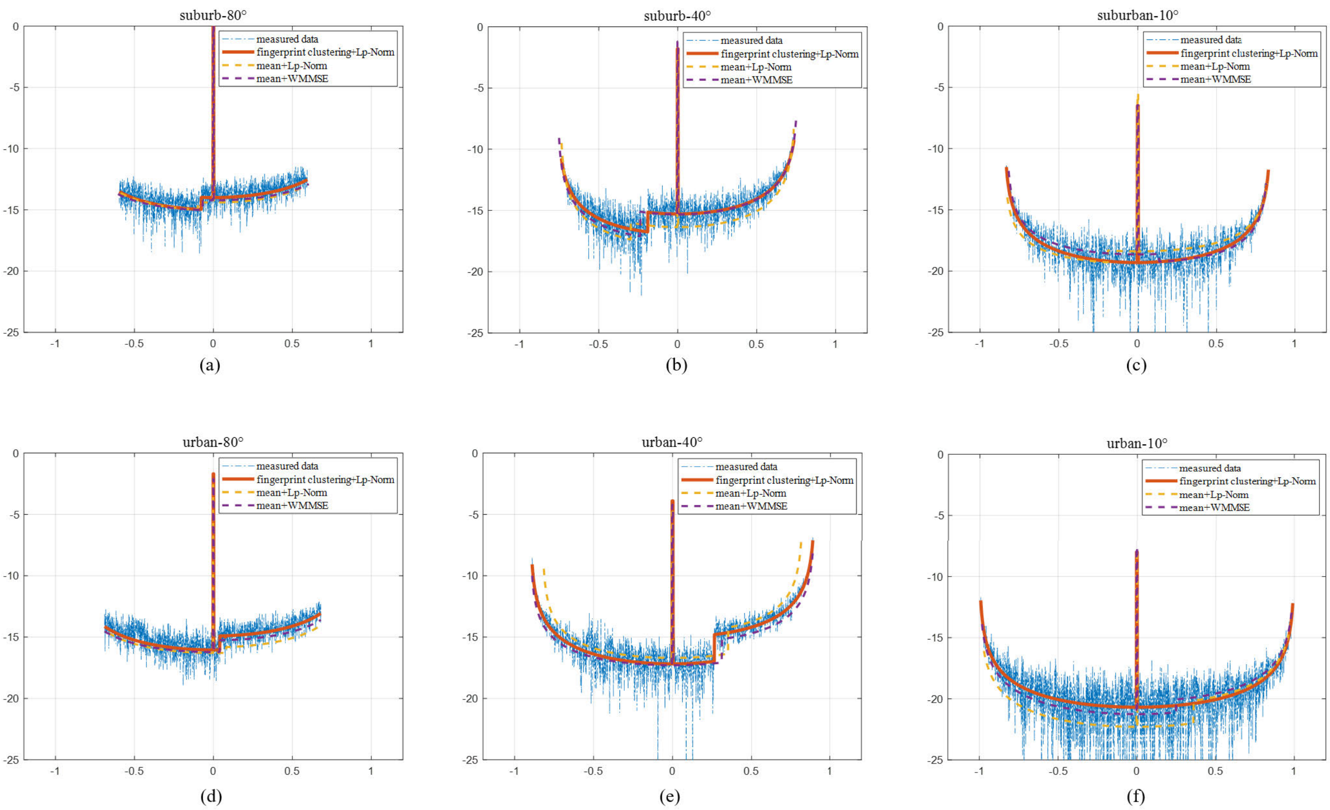

FIGURE 11. The fitting results of Doppler power spectrum model parameters under different scenes.

precision. When more scenes are divided or the amount of measurement data is larger, the interweaving between scenes will be closer, the probability of obtaining unexpected samples will be greater, and the ''aliasing phenomenon'' will be more serious. At this time, in order to ensure the accuracy of the model, it is important to classify the scene to select the reference data samples for model parameter fitting, so the advantages of the method proposed in this paper can be reflected.

Moreover, in order to prove the accuracy of the proposed tow-side truncated asymmetric model in describing the Doppler power spectrum of LEO satellite channel, we compare the proposed model with some existing troditional models. By calculating the RMSE between the measured data and these models, and comparing their values, the accuracy of the models can be judged. We take the scene composed of suburban environment at an elevation of 40° as an example, as shown in the Fig. 12 and Table 3. It can be seen that the model proposed in this paper is most consistent with the measured data. Jakes model does not consider the limited range of multi-path angle of arrival in LEO satellite channel, which leads to excessive Doppler spread.The shape of

TABLE 2. RMSE of the Doppler power spectrum model under different fitting methods.

Scenes		Mean+Lp-Norm [26]	Mean+ WMMSE [27]	Fingerprint clustering +Lp-Norm
Suburban	10°	0.82	0.42	0.16
	40°	0.32	0.26	0.13
	80°	0.24	0.20	0.09
Urban	10°	0.88	0.56	0.18
	40°	0.33	0.28	0.14
	80°	0.25	0.22	0.12

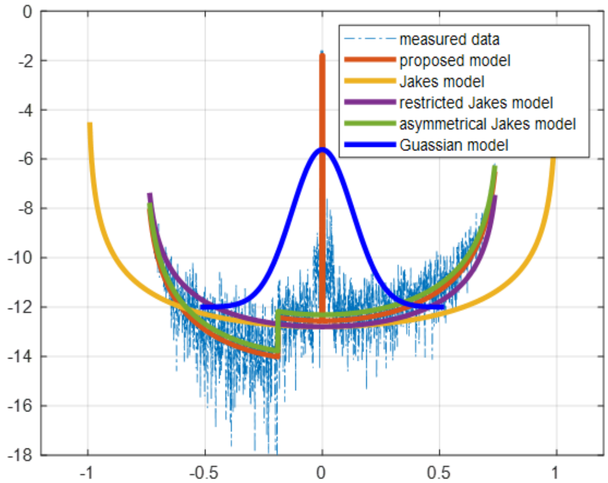

FIGURE 12. Fitting results between measured data and various Doppler power spectrum models.

TABLE 3. RMSE between measured data and various Doppler power spectrum models.

Proposed	Jakes	Restricted Jakes	Asymmetrical Jakes	Gaussian
0.13	0.56	0.29	0.20	0.92

Gaussian model is quite different from that of Doppler power spectrum of LEO satellite channel because of the difference of their multi-path angle of arrival distribution. The erro of the restricted Jakes model and asymmetric Jakes model is relatively small, but the restricted Jakes model does not consider the spectrum asymmetry caused by the blocking of scatterers in the channel, and both models lack the description of the effect of LOS component on Doppler power spectrum. Therefore, the proposed model can accurately describe the Doppler power spectrum of LEO satellite channel.

V. CONCLUSION

In this paper, a novel Doppler power spectrum modeling method for LEO satellite multi-communication scenes is proposed, which is used to accurately describe the Doppler power spectrum characteristics under the influence of channel time-varying strength and scene diversification during satellite transit. We draw the measured Doppler power spectrum data into the graphs, and extracted their shape features to construct the atlas fingerprints. Then, by fingerprint clustering, the reference data corresponding to the feature vectors with the strongest characterization ability in each category is selected to fit the model parameters, so as to obtain the concrete Doppler power spectrum model of each scene. This method can effectively solve the problems of large error and low model accuracy in the parameter fitting results of Doppler power spectrum model caused by rapid changes of multiple scenes in the process of LEO satellite channel measurement and modeling. The experimental results show that the model is in good agreement with the measured data. The modeling method we proposed can be applied to the modeling of not limited to narrowband or broadband channels, In addition, the atlas fingerprint method can provide new ideas for the research of LEO satellite channel modeling.

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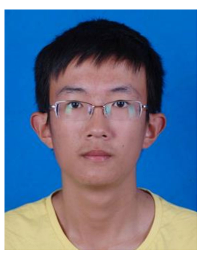

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