Wireless Channel Sparsity: Measurement, Analysis, and Exploitation in Estimation

Ruisi He, Bo Ai, Gongpu Wang, Mi Yang, Chen Huang, and Zhangdui Zhong

Abstract

Sparse channel arises in a number of applications in wireless communications such as channel estimation and signal processing. There is growing evidence that physical wireless channels exhibit a sparse structure, and channel sparsity has been even considered as a nature of channels in many recent research works. However, there still lacks a good measure of channel sparsity, and mostly the assumptions that channel is sparse or non-sparse are based on intuitive analysis without measurement validation, which leads to some contradictions. In this article, based on channel measurement data, it is pointed out that a widely-used assumption, that wireless channels can be considered to be sparse, has pitfalls. Without loss of generality, the measurements are conducted in an urban scenario with different degrees of channel multipath richness. The channel degrees of freedom, diversity measure, and the Ricean K factor are used to evaluate channel sparsity, and they are found to have fairly high accuracy of measuring degrees of channel sparsity. It is also observed from measurements that the degree of channel sparsity is not steady and a sparse channel may change to non-sparse within a short time/distance observation window. Moreover, sparse and non-sparse based channel estimators are evaluated based on the measurements and the performances are analyzed. The results show that a sparse channel estimator cannot guarantee stable estimation accuracy even in channels with a high degree of sparsity, and considerable performance degradation will occur if a channel changes to non-sparse, which actually often happens in realistic communication scenarios and should be carefully considered in performance analysis. Some sparse channel related technical issues are also discussed in the article.

Introduction

The subject of wireless communications is to transmit wireless signals from a source to one or more destinations. Of particular importance in the analysis and design of wireless communication systems are the characteristics of the physical wireless channels, which generally affect the design of the basic building blocks of communication systems. The following three features of wireless channels have attracted extensive attention: multipath effect, channel fading, and openness. Multipath effect gives birth to the technology of Orthogonal Frequency Division Multiplexing (OFDM); channel fading attracts investigations on diversity methods; and open feature leads to new research branches on security.

In recent years, channel sparsity [1], another characteristic of wireless channels, has attracted strong interest and much attention from both academic and industrial circles. The sparse structure of physical channel can be understood as follows:

- The number of multipath components (MPCs) in the environment is limited, especially for some scenarios with sparse scatterers and large propagation loss, such as millimeter wave (mmWave) communications.
- Wireless channels can be characterized by clustered MPCs, that is, MPCs can generally be divided into groups with similar characteristics, and the number of groups is often small [2].

In fact, a large number of existing channel models have used the above-mentioned sparsity hypothesis. For example, in the classical tapped delay line model, most of the energy in channel response can be included by using a small number of taps (generally no more than 20). Similarly, based on the assumption that MPCs exist in the form of clusters, many channel models based on cluster structure have been proposed. If wireless channels are sparse, not only the basic building blocks of communication systems, including sampling design, channel estimator, signal detector, and antenna deployment, but also the system architecture such as cloud radio access networks, will be largely different from the traditional ones and await further investigation.

One clear and direct influence of channel sparsity is channel estimation, since fewer training symbols are needed and new estimation algorithms are to be developed. It is also worth noting that in some scenarios sparse channel estimation is necessary [3]. For example, downlink channel state acquisition for frequency-division duplex wireless systems with massive multiple-input multiple-output (MIMO) has to explore channel sparsity in time, special or frequency domain so as to reduce the number of training symbols and also the amount of feedback overhead. For another instance, one popular method to estimate the fast time-varying channel parameters is to employ a basis expansion model (BEM). BEM decomposes the channel parameters into the superposition of the time-varying basis functions weighted by a few time-invariant coefficients, which is sparse representation of complicated channels.

Moreover, channel sparsity also has a strong impact on the existing channel data processing and channel modeling techniques. Compared to the

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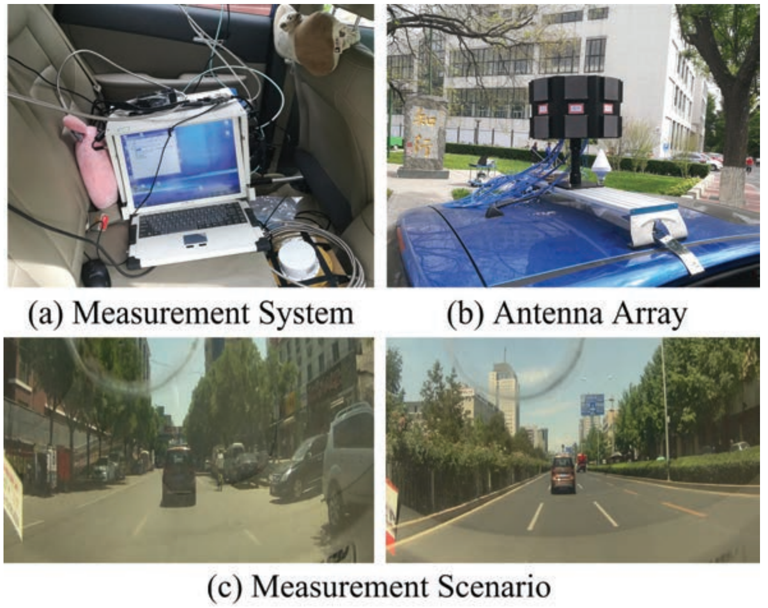

FIGURE 1. Measurement campaign.

non-sparse channel, the MPC clusters distribute differently in the spatial domain of sparse channels, and it leads to challenges to the clustering of MPCs. Due to the sparse distribution of clusters, the density of MPCs in each cluster may significantly increase considering the scatterings and diffractions especially in higher frequency bands. This may impact some clustering approaches based on the statistic feature of intra-cluster. For time-varying channels, the high density of MPCs in each cluster may also cause difficulties in tracking methods, which is a necessary procedure for analyzing the non-stationarity of time-varying channels. Consequently, the different characteristics of channel sparsity have an influence on modeling methods as well.

However, evaluating whether a channel is sparse or not is usually quite tricky. On one hand, densely distributed MPCs are often assumed due to the complex propagation environments and multipath propagation effect. On the other hand, a sparse structure is also assumed for the channel as some scenarios lack sufficient richness of MPCs in the propagation environments, especially for mmWave communications. Meanwhile, it is noteworthy that there still lacks a good measure of wireless channel sparsity and the both assumptions (the channel is sparse or non-sparse) are mainly based on intuitive analysis without measurement validation, which leads to some contradictions. For example, people mostly now consider a mmWave channel to be sparse; however, sparse channel estimation was proposed for general non-mmWave radio channels [4]. Underwater acoustic channels are considered to be sparse since underwater MPC is not contiguous but consists of isolated signal arrivals [5]; however, some research works indicate that the underwater acoustic environment provides a time-varying richly-scattered environment [6], that is, a non-sparse channel. Sparse channel estimation in ultra-wideband channels was motivated by the ability to resolve individual MPC or clusters in the channels [7]; however, densely distributed MPCs are observed based on ultra-wideband channel measurements [8]. In addition, people usually consider a channel to be sparse when the number of observed MPCs is small. However, this approach is found to be not accurate because it does not consider the impact of MPC power [9]. The evaluation of wireless channel sparsity is still a challenging task. It is also not clear whether a realistic channel exhibits sparsity according to measurements, and whether the scenarios with sparse or non-sparse channels are distinct. To fill the gap, this article presents measurement based analysis of channel sparsity in an urban vehicular scenario, and the measured data are used to evaluate whether a realistic channel is sparse and how the degree of channel sparsity changes in real propagation environments. The results show that even in a similar environment, the change of MPC structure significantly changes the degree of channel sparsity, and a sparse channel may change to non-sparse within a short time/distance observation window. Such phenomenon significantly affects the performance of sparse channel estimation algorithms in realistic communication environments. The obtained results are useful to understand channel sparsity in real propagation environments.

The rest of the article is organized as follows. The next section presents measurement-based channel sparsity evaluation. Then we present sparse channel estimation algorithms and analyze the performance using measurement data. Following that we discuss some sparse channel related technical issues in communications. Finally, we conclude the article.

Channel Sparsity

Measurements

To obtain channel data for analysis, a wireless channel measurement campaign was conducted as shown in Fig. 1, and the data are used for sparsity measure evaluation and channel estimation. The data were obtained in an urban scenario in Beijing, China. The transmitter (Tx) and receiver (Rx) antennas were placed on top of two vehicles with a height of 1.7 m, and the two vehicles were moving in the same direction with an average speed of 60 km/h (16.7 m/s). An omnidirectional microstrip antenna was used at Tx and a 16-element cylindrical antenna array was used at Rx as shown in Fig. 1b. The data were measured by using a self-designed channel sounder using components from National Instruments as shown in Fig. 1a, which mainly includes a vector signal generator at Tx and a vector signal analyzer at Rx. The carrier frequency was 5.9 GHz and the bandwidth was 30 MHz. 513 frequency points were measured in each snapshot. The transmitted signal power was 34 dBm and the average signal-to-noise-ratio was approximately 24 dB. During the measurements, the Tx-Rx distance was around 25 m, although it varied due to road conditions. More details of the channel sounding system can be found in [10]. We selected 49 different positions from the channel measurements for analysis. Since the vehicular environment has fairly high dynamics due to the movements of Tx/Rx and scatterers, the channel is time-varying and different degrees of channel sparsity are expected as shown in Fig. 1c, where the densities of scatterers are different, which allows us to better analyze the impact of channel sparsity.

Channel Sparsity Evaluation

Accurately measuring channel sparsity has been a challenging task because there is no ground-truth of channel sparsity, and a suitable measure is still missing to evaluate the degree of channel sparsity. According to the signal processing viewpoint, a sparse representation of signals implies that a small number of elements in data contain a large proportion of the energy of the data. As suggested in [9], the channel degrees of freedom (DoF), diversity measure, and the Ricean K factor are used to evaluate the change of channel sparsity based on channel measurements. The DoF is defined as the rank of channel correlation matrix, which can be estimated by the eigenvalues for a noisy channel. The diversity measure identifies the eigenvalue spread of the channel correlation matrix. The Ricean K factor is defined as the ratio of the power of the dominant component to the power of the remaining components in the channel.

Figure 2 shows the relations of the estimated values of DoF, diversity measure, and Ricean K factor based on the measurements. It is found that the DoF increases with the diversity measure and the trend is generally linear with a cross-correlation coefficient of 0.96. A sparse channel generally exhibits fewer channel DoF and diversity measure, and this implies that both the DoF index and diversity measure are fairly accurate and sensitive to the change of channel sparsity. According to [9], the measured channels with low estimated values of DoF and diversity measure can be considered to be sparse. Moreover, it is observed in Fig. 2 that the estimated Ricean K factor decreases with the diversity measure and the corresponding cross-correlation coefficient is –0.47. The Ricean K factor is the ratio of the power of the dominant component to the power of the remaining components. According to the classic sparse representation that a small number of elements contain a large proportion of the total energy, a high value of K factor corresponds to a sparse channel. However, the cross-correlation between K factor and diversity measure is relatively low, and this implies that using DoF and diversity measure will have higher accuracy to measure channel sparsity.

Figure 3 shows the continuous changes of DoF and diversity measure during the measurements. The similar trend of the two curves in Fig. 3 verifies that they are positively correlated. Another important observation is that both DoF and diversity measure exhibit fairly high variations during the measurements, which implies that in realistic wireless channels, the degree of channel sparsity is not steady and it is significantly affected by the propagation channel characteristics. Even in a similar environment, the change of MPC structure and distribution may significantly change the degree of channel sparsity. A sparse channel may change to non-sparse within a short time/distance observation window. Therefore, the assumption that channel is always sparse in certain scenarios may be questionable. Actually, we find that the dynamic of channel sparsity is much higher than it was reported, and this results in further challenges to the sparse channel estimation algorithm.

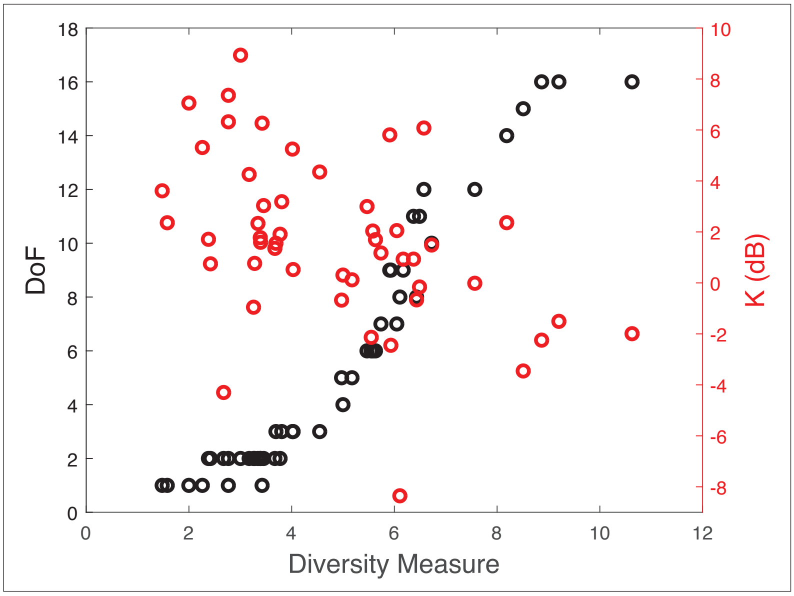

FIGURE 2. Relations of the estimated values of DoF, diversity measure, and Ricean K factor based on the channel measurements.

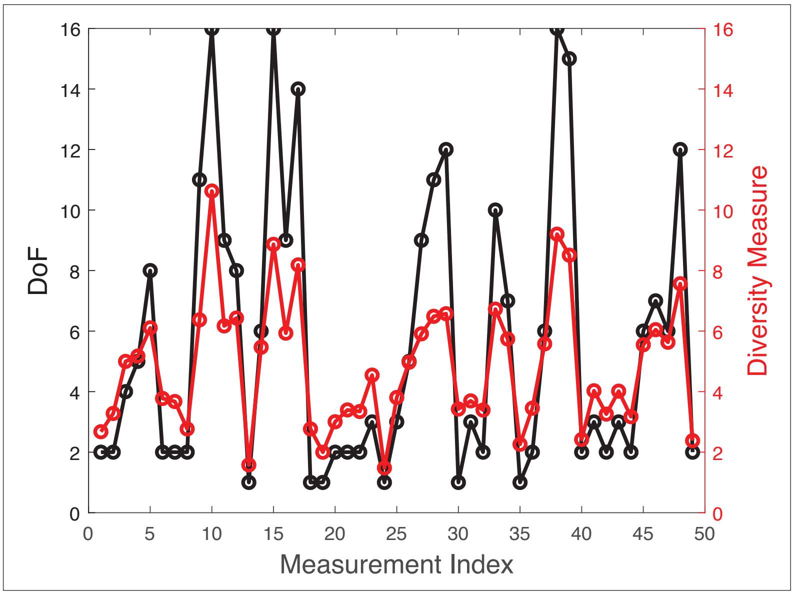

FIGURE 3. Continuous changes of the estimated values of DoF and diversity measure during the channel measurements.

Channel Estimation

Sparse Channel Estimation Algorithms

The typical mathematical model for wireless communication systems can be expressed as $\boldsymbol{y} = \boldsymbol{Sh} + \boldsymbol{w}$, where $\boldsymbol{S}$ denotes the training sequence, $\boldsymbol{h}$ represents the wireless channels to be estimated, and $\boldsymbol{w}$ is the noise item often assumed as Gaussian. There are two traditional estimators to obtain $\boldsymbol{h}$ from the received signals $\boldsymbol{y}$ when the training sequence $\boldsymbol{S}$ is known [11]: the least square (LS) estimator $\hat{\boldsymbol{h}} = (\boldsymbol{S}^H\boldsymbol{S})^{-1})\boldsymbol{S}^H\boldsymbol{y}$ and the linear minimum mean square error (LMMSE) estimator $\hat{\boldsymbol{h}} = \boldsymbol{R}_h\boldsymbol{S}^H(\boldsymbol{S}\boldsymbol{R}_h\boldsymbol{S}^H + \boldsymbol{R}_w)^{-1}\boldsymbol{y}$. Here, $\boldsymbol{R}_h$ and $\boldsymbol{R}_w$ are the correlation matrices of the channels $\boldsymbol{h}$ and the noise $\boldsymbol{w}$, respectively. In summary, the LS estimator treats the channels $\boldsymbol{h}$ as constants and does not require any prior information about noise, while the LMMSE estimator considers the channels $\boldsymbol{h}$

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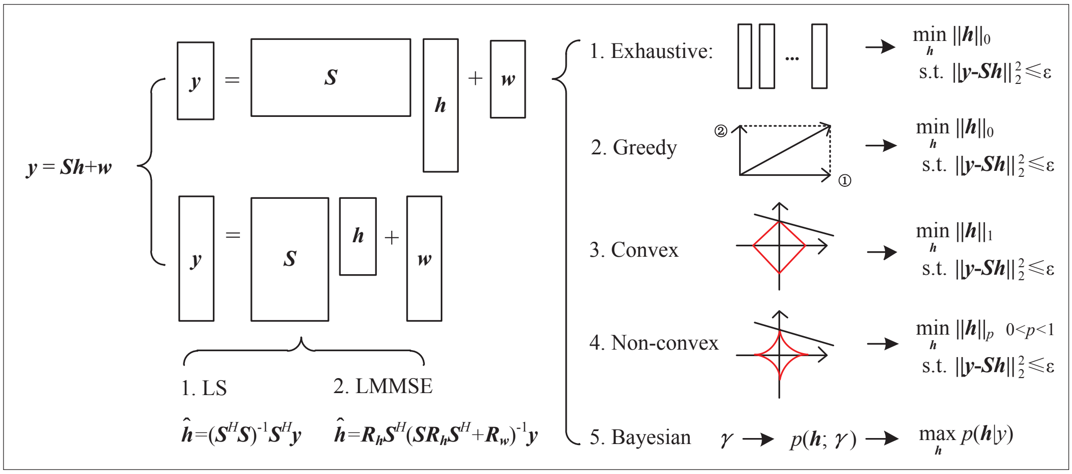

FIGURE 4. Traditional and sparse channel estimators.

as random variables and needs the second-order statistics of both channels $\boldsymbol{h}$ and noise $\boldsymbol{w}$.

When channels $\boldsymbol{h}$ are sparse, that is, the vector $\boldsymbol{h}$ contains many zero elements, sparse channel estimators can be motivated. Generally speaking, there exist five classes of sparse channel estimators [12]: exhaustive search, greedy pursuit, convex relaxation, non-convex approximation and optimization, and Bayesian approach. Figure 4 illustrates all these estimators.

An exhaustive search estimator lists all possible sets for the vector $\boldsymbol{h}$ from which to obtain the one that can minimize $\|\mathbf{y} - \mathbf{Sh}\|_2^2$. Clearly, such a method can find the optimal solution at the cost of large time complexity even when certain pruning strategies are adopted. Accordingly, the exhaustive search estimator is often limited to small-scale problems.

A greedy pursuit estimator utilizes greedy strategy to obtain the currently optimal choice and then iteratively finds the next components. For instance, the orthogonal matching pursuit (OMP) method, a classic greedy pursuit estimator, first normalizes the training matrix $\mathbf{S}$, identifies the component that produces the greatest improvement and subtracts its impact from the vector $\mathbf{y}$, and then repeats the above process so as to successively obtain the next components.

A convex relaxation estimator replaces the non-convex constraint $\|\mathbf{h}\|_0$ with convex ones such as $\|\mathbf{h}\|_1$ and later exploits some features to solve the convex problem. The final solution is globally optimal for the transformed convex problem but locally optimal for the original non-convex problem.

A non-convex estimator approximates the zero norm condition $\|\mathbf{h}\|_0$ as $\|\mathbf{h}\|_p$ $(0 < p < 1)$ which can be further transferred as one non-convex problem where a stationary point can be located. For example, the optimization of $\|\mathbf{h}\|_p$ can be transformed as a weighted $\|\mathbf{h}\|_2^2$ optimization problem whose solution can be obtained iteratively.

A Bayesian estimator assumes the channels $\boldsymbol{h}$ as random variables with parameterized prior sparse distribution and designs a maximum a posteriori estimator, that is, $\max_{\boldsymbol{h}} p(\mathbf{h}|\mathbf{y})$. In the case of Gaussian signals, Bayesian estimators aim to calculate $E(\mathbf{h}|\mathbf{y})$ as the channel estimates.

In summary, exhaustive search estimators achieve optimal solutions at the cost of time; greedy, convex, and non-convex estimators use approximation strategy to obtain suboptimal or optimal solutions; while Bayesian estimators preset prior information for channel parameters and motivate Bayesian philosophy. Every type of the five estimators has its wisdom and merits as well as disadvantages. Given one sparse channel estimation problem, it is a challenge to choose one that can obtain the best estimation performance within an acceptable time period. Few studies provide practical measurement data to test and compare these estimators, which is investigated in the following subsection.

Implementation and Results

As mentioned previously, the channel was measured for 49 different positions in an urban scenario. In each position, we have obtained channel parameters from the 16 Rx antenna elements, and each channel consists of 513 channel paths. That is, we have a three dimensional channel matrix with 49 × 513 × 16 parameters. Let n denote the position order and suppose the kth antenna transmit symbols $s(n, k)$ through an Orthogonal Frequency Division Multiplexing (OFDM) scheme. Assume the transceivers have perfect synchronization, we can have the basic simplified system model $\mathbf{r} = \mathbf{Sh} + \mathbf{w}$, where $\mathbf{r}$ is the received OFDM symbols consisting of $r(n, \boldsymbol{k})$, $\mathbf{S}$ represents the transmitted symbol matrix constructed by $s(n, k)$, $\mathbf{h} = [h_1, h_2, ..., h_N]^T$ is the flat-fading channels to be estimated and $N = 49$, and $\mathbf{w}$ denotes the noise. Clearly, the goal is to obtain the channel estimates $\hat{\boldsymbol{h}}$.

When the channels $\boldsymbol{h}$ are sparse in some respect, we can further have $\boldsymbol{h} = \boldsymbol{B}\mu$, where $\boldsymbol{B}$ is the orthonormal transformation basis matrix and vector μ contains many zero elements. One special case is that the length of vector μ is much less than that of $\boldsymbol{h}$. The vector $\boldsymbol{h}$ is said to be d-sparse in the $\boldsymbol{B}$ domain if vector μ contains only d nonzero elements. Accordingly, we can obtain $\boldsymbol{r} = \mathbf{S}\boldsymbol{B}\mu + \mathbf{w}$. Clearly, the goal is to estimate the sparse vector μ. There exist two key problems in estimating μ. One is to determine the matrix $\boldsymbol{B}$ and the other is to decide the value of d. We address the two problems as follows.

We first calculate the correlation matrix $\boldsymbol{R}$ of the channel parameters from 49 positions, and then apply eigen-decomposition to the correlation matrix $\boldsymbol{R}$. We then choose the normalized eigenvector matrix of $\boldsymbol{R}$ as the basis matrix $\boldsymbol{B}$. Next, for each position, we check the eigenvalues of the channel correlation matrix $\boldsymbol{R}$ so as to set the values for d. Specifically, we set a threshold through locating the first d eigenvalues that account for 99 percent of the sum of all eigenvalues. Subsequently, we set the training number the same as d and utilize both traditional and sparse estimator to obtain the channel estimates $\hat{\boldsymbol{h}}$. We choose LS as the traditional estimator due to its simplicity and no requirement of any prior information. We first estimate the channel parameters corresponding to the pilots through LS and then recover other channel parameters through linear interpolation. On the other hand, we choose the OMP algorithm as our sparse estimator. We first obtain the estimate $\hat{\mu}$ and then recover the channels $\hat{\boldsymbol{h}} = \mathbf{B}\hat{\mu}$. Finally, we choose the mean square errors (MSEs) for the channel as the figure of merit. We plot MSEs versus measurement positions in Fig. 5. It can be observed that the MSE performance of the sparse channel estimator significantly varies at different positions, while the traditional estimator has relatively stable MSEs. It indicates that realistic channels generally have various degrees of channel sparsity for different positions, which will result in large variation at MSEs for the sparse channel estimator and small variation at MSEs for the traditional LS estimator. In other word, even though the sparse channel estimator can achieve better performance for the channels with high degree of sparsity, considerable performance degradation will occur if the channel changes to non-sparse, which actually often happens in realistic communication scenarios.

We also show MSEs versus channel DoF in Fig. 6. It can be seen that the traditional LS estimator generally has similar performance when DoF increases and it is not significantly affected by the degrees of channel sparsity, which follows the results in Fig. 5. However, the performance of the sparse channel estimator somehow decreases when DoF increases, which further validates that when the channel changes to non-sparse, the performance of the sparse channel estimator is degraded. The LS estimator mostly outperforms the sparse channel estimator in the case of large channel DoF. Meanwhile, Fig. 6 also shows that the sparse channel estimator has various performances when the channel DoF is small. The reason is that we choose the OMP based sparse estimator that cannot guarantee stable estimation accuracy. Different sparse estimators produce diverse performances even when channels are sparse and fixed, which implies that the choice of sparse channel estimator is one key deciding factor in estimation performance.

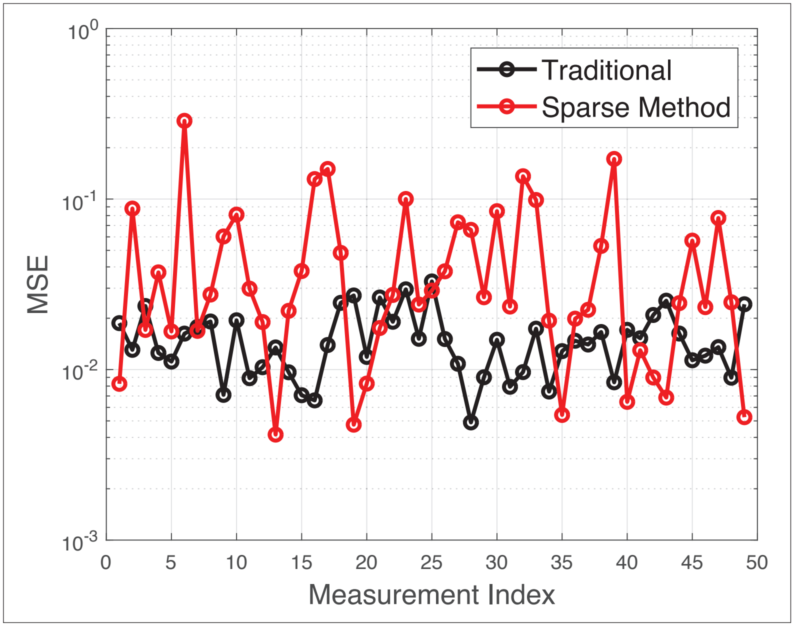

FIGURE 5. MSEs versus measurement positions for the traditional and sparse channel estimators using the measurement data.

Discussions

Impact of Measurement

We usually need channel measurements to obtain data for evaluating channel sparsity. However, the measurement configuration significantly affects sparsity evaluation. For example, many recent measurements show that the dense multipath component (DMC) scatterings from environments are significant, and they usually lead to non-sparse channels [13]. However, the extraction of DMC depends on transmit power and dynamic range of the channel sounder. If transmit power is low, the DMCs are merged into the noise floor and the channel shows sparsity; if transmit power is increased and dynamic range of the sounder is fairly large, the DMCs can be measured and the channel may be non-sparse. It is thus challenging to distinguish sparse channels based on physical propagation and system configuration.

Sparse Channel Sounding

For massive MIMO channel sounding, because of its large array size and the resulting non-stationarity in the local space of the array, the sparse MPCs in space will aggravate the difference of signals received by different antenna elements of the array. Therefore, the influence of channel sparsity should not be ignored when designing massive MIMO channel sounders. In addition, for virtual MIMO channel sounders using a 3D rotating platform and directional antennas, channel sparsity can be used to optimize the testing process and reduce measurement time consumption.

Channel sparsity can also be exploited for data acquisition of the channel sounder. For ultra-wideband and dynamic channel measurements, the large bandwidth (>1 GHz) and high snapshot acquisition speed usually make channel sounders face difficulties in data acquisition, storage and transmission. For sparse channel measurements, characteristics of sparse signals can be used based on compressed sensing theory. Specifically, a smaller sampling rate can be used and the signal can be perfectly reconstructed by using a nonlinear reconstruction algorithm, thereby realizing efficient and low-complexity data acquisition.

Sparse Channel Modeling

Different with the non-sparse channels, the path loss and attenuation of reflection, scattering, diffusion and penetration of the sparse channels are generally increased because of the reduced MPCs. In other words, signal power decays faster with propagation distance in sparse channels,

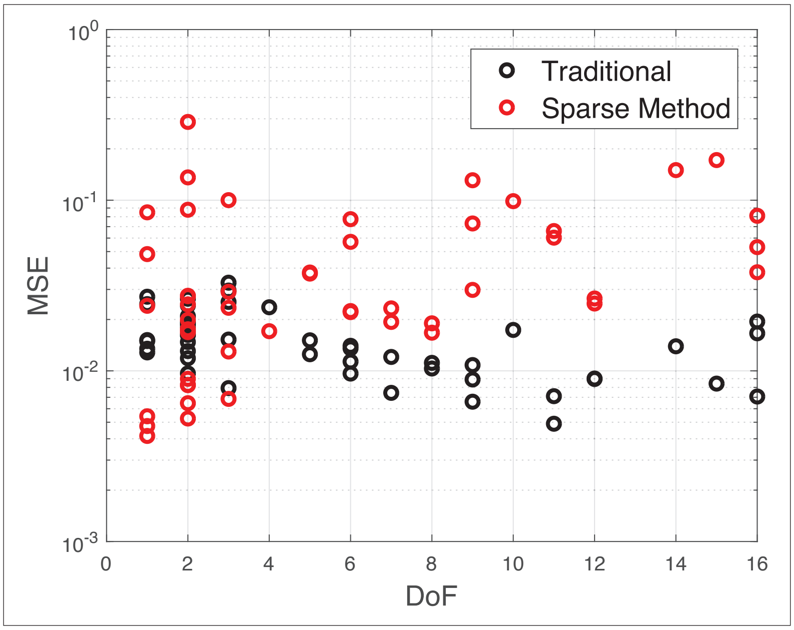

FIGURE 6. MSEs versus channel DoFs for the traditional and sparse channel estimators using the measurement data.

where some MPCs cannot be further detected due to the low power. As a result, the sparse channels show more distinct cluster-based structure, where only dominant clusters can be well observed. The number of MPCs inside each cluster has impact on the statistical distribution of MPCs. Hence, the inherent characteristics of the sparse channels bring a new challenge to channel characterization. Moreover, since sparse channels generally show a distinct cluster structure, some classic clustering algorithms with low complexity may have good performance, and the sparse cluster structure may lead to a low-complexity channel model, which concentrates more on dominant components in channels.

Sparse Channel Estimation

It is true that sparse sensing based channel estimation can save training symbols, reduce feedback overhead and improve system performance. However, it is an open challenge to tell if the channels are sparse in certain domains or not. These domains can be time, frequency, spatial, or some specially defined space. Consequently, choosing which type of channel estimator is the next challenging problem. How to design an optimal training sequence and how many gains can be obtained with optimal estimators are also unknown issues that are worth further investigation. Moreover, the communication scenario also has an impact on the use of channel sparsity. For example, in high speed railway communications, sparse channels can be better predicted since a strong line-of-sight path exists and trains run on fixed tracks. Therefore, it is possible to design compressed sensing estimators that explore channel sparsity related with environments and space.

Sparse Channel Beam Selection

Compared to the non-sparse channel, the sparse channel shows a significant difference in the space domain or even the frequency domain as well. For beam selection, pros and cons come with these new channel properties. The ultimate goal of beam selection is to avoid the interference between different terminals through beamforming. Meanwhile, how to select and continue tracking the beam with an appropriate computation complexity is always an essential problem. Benefitting from the sparsity of the channel in the space domain, the distinctive cluster distribution makes interference management easier, which leads to a relatively lower computation complexity of beam selection. Nonetheless, a sparse channel also means limited choices of beam selection for each terminal. As a result, terminals no longer have various accessible beams. This brings more difficulties for the network to achieve a theoretical performance boundary. Therefore, new optimization of channel resources considering channel sparsity are needed.

Intelligent Channel Sparsity Identification

In order to efficiently apply the designed sparse-channel-based algorithms and techniques, it is necessary to accurately identify the channel sparsity state. Under such conditions, channel estimation can be further enhanced and improved by using the accurate real-time state of channel sparsity. For practical communication systems, two issues should be considered for sparse channel identification:

- Accuracy: the system needs to accurately identify whether the current channel is sparse and what is the degree of sparsity.
- Real-time: for communication in dynamic channels, the system needs to be able to sense the change of channel sparsity in real-time.

An expected solution is to drive the intelligence of sparse channel identification based on artificial intelligence. Sparse channel identification can be generally considered as a classification problem, which can be well solved by machine learning. Test data collected in various environments with known sparsity can be used as training datasets, and intelligent algorithms can be used to train sparsity identification models. The obtained model can be used to realize real-time and accurate channel sparsity identification.

Conclusion

In this article, measurement based channel sparsity analysis and estimation are presented. The work focuses on evaluating whether a realistic channel is actually sparse and how the degree of channel sparsity changes in real propagation environments. The data measured in a vehicular urban scenario are used, which include fairly rich degrees of MPC richness. Considering the challenges of accurately measuring channel sparsity, three indicators of DoF, diversity measure, and the Ricean K factor are used to evaluate channel sparsity jointly. The LS and OMP based channel estimations are conducted using the measurement data, representing sparse and non-sparse channel estimations, respectively. The results show that the dynamic of channel sparsity is much higher than it was reported before, and mostly, the scenarios with sparse or non-sparse channels are *not* distinct. Even though the sparse structure of a channel has been widely assumed before, it should be carefully used because for real propagation channels, the degree of channel sparsity is not steady and a sparse channel may change to non-sparse within a short time/distance observation window. In such a case, considerable performance degradation will occur for a sparse channel estimator. Even in sparse channels, the sparse channel estimator cannot guarantee stable estimation accuracy. Finally, the impacts of channel sparsity on channel measurements and modeling, estimation, and beam selection are further discussed and insights are presented. The results in the article can be used to better understand channel sparsity in real propagation environments and further improve the use of a sparse channel in wireless communications. We encourage further measurement-based validations of channel sparsity and the impacts on channel estimation in various frequency bands and propagation scenarios.

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Acknowledgments

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