Multi-user MIMO Communications with Interference Mitigation in Time-varying Channels

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Abstract—**In this paper, we present a scheme for realizing reliable multi-user MIMO communications in the presence of interference in time-varying channels. The null space of interfering channels is estimated and exploited for interference mitigation. We first introduce an improved superframe structure to enable frequent tracking of user channels and the null space of interfering channels. The different natures of the received user signals and interference require different processing methods. We improve and compare several adaptive equalizers to deal with time-varying user channels, and propose to use a subspace-based tracking algorithm to handle time-varying interfering channels. Simulation results are provided and validate the effectiveness of the scheme.**

I. Introduction

Tactical wireless communication systems operate in complex terrain and radio frequency (RF) contested environments. These systems should be robust to both intentional and hostile interference, while enabling high data rate communication between end devices. Compared to single antenna systems, multiple-input-multiple-output (MIMO) techniques can significantly increase system capacity and mitigate interference in the spatial domain, and they have been proposed for tactical communications [1]–[4]. MIMO provides great potential for interference mitigation, achieving reliable and high-speed communications.

Numerous MIMO-based interference mitigation methods have been investigated in tactical RF environments [5]–[10]. For example, in [5], an adaptive transmit-receive beamforming scheme was proposed for MIMO system, using subspace projection to determine the transmitter and receiver beamforming. An anti-jamming method in [7] was developed based on null-steering to cope with adverse interference in Long Term Evolution (LTE) military communications. In [8], a tactical MIMO communication system was developed to mitigate interference from multiple interferers. More recently, we proposed a scheme for joint multi-user MIMO (MU-MIMO) communication and adverse interference mitigation [10]. Different to conventional approaches which estimate the directions of interferers and then generate beams with nulls in these directions, we designed an approach based on the null space of estimated interfering channels. This method can effectively deal with interfering signals coming from multiple directions, and can potentially support communications with users even when they are in similar directions to the interferers.

Practically, both users and the interferers may move around, and the environment between them is likely to be dynamic. This leads to time-varying channels, which are typically challenging to deal with. Time-varying channels require frequent updates on null space estimation, channel estimation and equalization coefficients. The user channels and interfering channels are different in nature. The user channels can be estimated exactly and the signals from other users can be potentially removed because all users' signals are based on normal constellation symbols. However, the interfering channels cannot be directly estimated because the interfering signals can be any type, even without a fixed correlation. The estimate will depend on both the channel and the transmitted signals. Since the statistical properties of the interfering signals can be time-varying, the effect of the signal cannot be removed effectively using existing blind channel estimation techniques. One effective way is to estimate the null space of the interference channels instead, to mitigate the interfering signals. However, the null space estimation is based on the received signal, and it is still affected by the correlation of the interfering signals. When either the interfering channels or signals change, the null space still needs to be updated. Otherwise, the residual interfering signals may increase. Furthermore, we assume that the interference is similar to additive white Gaussian noise (AWGN). Therefore we cannot use an adaptive equalizer to deal with both user and interference channel variations.

In this paper, we propose a scheme including several techniques to address the problems associated with time-varying user and interferer channels. We propose an improved superframe structure to enable effective channel and null space tracking. We then improve and compare several existing adaptive equalizers to deal with time-varying user channels, and introduce a subspace-based tracking algorithm to handle time-varying interfering channels. Simulation results are provided and validate the effectiveness of the scheme.

Notations: We use $(.)^T$, $(.)^*$, $(.)^H$, and $(.)^{-1}$ for transpose, conjugate, conjugate (Hermitian) transpose, and inverse operation, respectively.

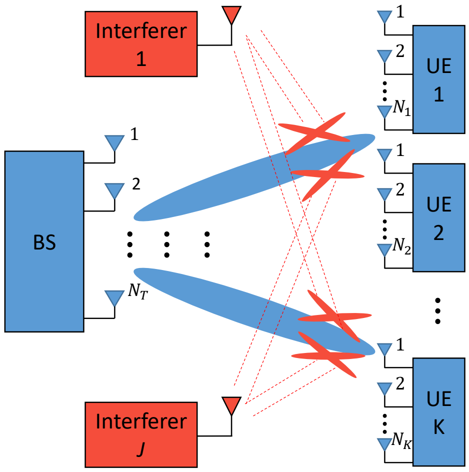


Fig. 1: MU-MIMO system with active interferers.

II. System Model and Basic Receiver Signal Processing

In this section, we present our scheme by referring to an access network with multiple user equipment (UE) and a base station (BS), and we focus on the downlink, i.e., the BS sends multiple spatial streams to multiple users. The scheme can also be applied to other networks such as an ad-hoc network where one node uses MU-MIMO to communicate to multiple other nodes in the presence of active interferers. Consider such an MU-MIMO downlink system in an RF contested environment, with N_T transmit antennas at the BS and N_k receive antennas at the k^{th} UE, as illustrated in Fig. 1. The BS communicates to K UE using MU-MIMO. Note that the BS does not necessarily have more antennas than UE.

There are J single-antenna active interferers that intend to interfere with the communications between the BS and the UE by continuously transmitting interference signals. Note that the algorithms discussed in this paper are also suitable for multi-antenna interferers, and an interferer with multiple antennas can be considered as multiple single-antenna interferers. For both cases, we assume there are a total of J antennas of interferers' in the system.

The number of independent data streams for the k^{th} UE is S_k, where $S_k \le N_k$, and $S = \sum_{k=1}^{K} S_k$ is the total number of independent streams. Note that at the minimum, we only require $N_T \ge S$ for MU-MIMO, and $N_k > J$ for effective interference mitigation and signal reception. In reality, due to the channel correlation between antennas, the number of supported streams is generally reduced. We do not require channel reciprocity here. The channel in each communication link of the dynamic environment including motion is assumed to be a time-varying Rician fading channel.

At the sample time t, the received signals at the k^{th} UE is given by

$$\begin{aligned}\mathbf{y}_k(t) = \quad & \mathbf{H}_k(t)\mathbf{P}_k\mathbf{s}_k(t) + \mathbf{H}_k(t)\textstyle\sum_{i\neq k}^{K}\mathbf{P}_i\mathbf{s}_i(t) \\ & +\mathbf{Z}_k(t)\mathbf{x}_{\mathrm{j}}(t) + \mathbf{n}(t),\end{aligned} \tag{1}$$

where $\mathbf{P}_k \in \mathbb{C}^{N_T\times S_k}$ is the precoding matrix applied at the BS for the k^{th} UE, $\mathbf{H}_k \in \mathbb{C}^{N_k\times N_T}$ denotes the channel matrix between the BS and the k^{th} UE, $\mathbf{s}_k \in \mathbb{C}^{S_k\times 1}$ denotes the signal from the BS to the k^{th} UE, N_{sample} is the number of signal samples, $\mathbf{Z}_k = [\mathbf{Z}_{k1}, \mathbf{Z}_{k2}, ...\mathbf{Z}_{kJ}] \in \mathbb{C}^{N_k\times J}$ is the channel matrix between J interferers and the k^{th} UE, $\mathbf{x}_{\mathrm{j}} = [\mathbf{x}_{\mathrm{j}1}; \mathbf{x}_{\mathrm{j}2}; ...\mathbf{x}_{\mathrm{j}J}] \in \mathbb{C}^{J\times 1}$ stands for the transmitted interference signals, and $\mathbf{n} \in \mathbb{C}^{N_k\times 1}$ is additive white Gaussian noise (AWGN) with independent and identically distributed (i.i.d.) entries of zero mean and variance σ_n^2.

The precoder can be designed based on equivalent channels fed back from the UE. This can improve the system performance, including both detection performance and increased number of spatial streams when $N_T > N_k$. However, using an explicit feedback timeslot will significantly increase the time period of the transmission, which may become infeasible in fast time-varying channels. Therefore direct communication without explicitly requesting and waiting for channel feedback is preferred. The resulted number of spatial streams will be reduced in this case. Without loss of generality, we assume the precoder matrix $\mathbf{P}_k$ is known. In the case of no channel knowledge, this can be a submatrix of the Walsh-Hadmard matrix with an evenly distributed data symbol in all antennas [11].

To guarantee communications between the BS and the UE, the MU-MIMO system needs to mitigate the interference signals. In the null space based approach, this is achieved by multiplying the received signal with a beam-forming matrix derived from the null space matrix of the interference channels. The received signal after nullification can be represented as [10],

$$\begin{aligned}\mathbf{r}_k(t) =& (\mathbf{W_k(t)})^H\Big(\mathbf{H}_k(t)\mathbf{P}_k\mathbf{s}_k(t) \\ & + \mathbf{H}_k(t)\sum_{i\neq k}^{K}\mathbf{P}_i\mathbf{s}_i(t) + \mathbf{Z}_k(t)\mathbf{x}_{\mathrm{j}}(t) + \mathbf{n(t)}\Big),\end{aligned} \tag{2}$$

where $(\mathbf{W_k(t)})^H \in \mathbb{C}^{S_k\times N_k}$ is the beam-forming matrix used to nullify the received interference signals.

A straightforward method is to let $\mathbf{W(t)}$ be the estimate of the null space matrix of $\mathbf{Z}_k(t)$, $\hat{\mathbf{Q}}_k$.Equalization can then be applied to the signal $\mathbf{r}_k(t)$ to recover the data symbols $\mathbf{s}_k(t)$.

III. The Proposed Methodology

In this section, we present the proposed scheme for realizing reliable MU-MIMO communications in the presence of hostile interferers in time-varying channels. We first present a design of the superframe that enables tracking of UE channels and null space of interfering channels. We then introduce adaptive signal processing techniques, to support the dynamic use case of mobile UE with time-varying null space of interfering channels.

A. Structure of the Proposed Superframe

The proposed superframe is shown in Fig. 2. It consists of an initial and long silent period for null space acquisition, and several packets/frames. Within each packet and between packets, there is a short silent period for null space tracking and updating. The reason for using silent periods is that

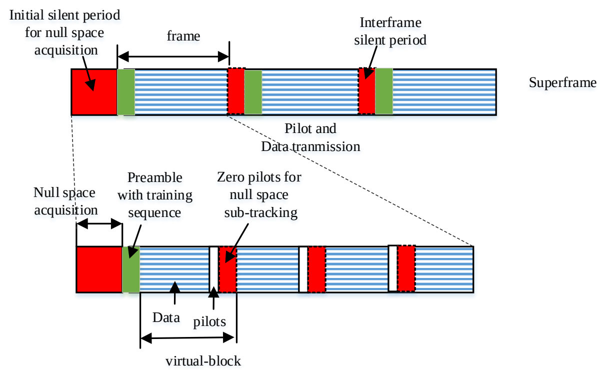


Fig. 2: Improved superframe structure for time-varying UE and interfering channels.

signals transmitted from the BS cannot be removed from the received signals to conduct null space estimation before channel estimation is done, as channel estimation needs to be based on the signals in equation (2).

Each frame consists of a preamble and many blocks. Each block consists of symbols of data payload (including PHY header), one conventional pilot, and several zero pilots. The preamble includes a short training sequence (STS) and a long training sequence (LTS). The STS is used for packet detection and fine timing, and carrier frequency offset (CFO) estimation. The LTS is used for channel estimation. The conventional pilots are used for updating equalization coefficients, and the zero pilots (no transmitted signals) are used for null space tracking.

The use of pilots and zero pilots enables effective tracking of both the UE channels and null space. It is noted that channel estimation, and hence the equalization coefficients, also need to be updated once the applied null space matrix $\mathbf{W}_k(t)$ is changed. So the change of $\mathbf{W}_k(t)$ should generally be applied at the start of each frame, but not after each segment of zero pilots.

B. Adaptive Channel Equalization

To deal with time-varying UE channels, we propose to use an adaptive equalizer, where the equalization coefficients can be adapted to channel variations.

There have been several types of adaptive filters proposed in the literature, such as the conjugate gradient equalizer (CGE) for broadband MIMO systems in [12], and the adaptive decision feedback equalizer (DFE) for V-BLAST systems in [13]. All of these equalizers recursively compute and update equalization coefficients. The CGE does not require matrix inversion, and has a lower complexity and better numerical stability. The DFE can achieve better performance, but has a higher complexity.

In this paper, we test and compare the equalizers in [12] and [13] for all the dynamic use cases presented here, with some improvements detailed below.

1) Improvement on Initialization: Most of these adaptive equalizers consider the case without a training sequence block, and hence the initial values of the iterative algorithms are set as random or zero values. This causes long convergence time.

Since there is a sequence of training symbols in our proposed superframe structure, we can generate the initial inputs for equalizer coefficients, using, e.g., the LTS. The correlation matrix between received signals, between received signals and the data symbols and so on, can all be initialized using the received LTS signals. The performance of the adaptive filters is found significantly improved with the proposed initialization.

2) RLS-FFE: The DFE in [13] is based on the recursive least square (RLS) algorithm. It uses both feedforward and feedback filtering, and requires the reordering of DFE operations. Hence it has very high complexity. A lower-complexity filter can be derived from it by removing the feed-backward filter and keeping the feed-forward filter. We call it RLS-FFE. This achieves significantly reduced complexity, and is shown to work well via simulation.

C. Estimation of the Null Space Matrix

During the initial silent period (null space acquisition period) , the estimate of the null space matrix $\hat{\mathbf{Q}}_k$ can be obtained by using singular value decomposition (SVD) of the received interfering signals. Assume the interference channels and signals are fixed during a period of T samples. From (1), the received signal at the k^{th} user at sample t can be represented as

$$\mathbf{y}_{\mathrm{j}_k}^{\mathrm{est}}(t) = \mathbf{Z}_k \mathbf{x}_{\mathrm{j}}(t) + \mathbf{n}(t), \tag{3}$$

where $\mathbf{x}_{\mathrm{j}}$ is the vector of transmitted interference signals in the estimation process. Let

$$\mathbf{R}_k^{\mathrm{est}} = \frac{1}{T} \sum_{t=t'}^{t'+T} \mathbf{y}_{\mathrm{j}_k}^{\mathrm{est}}(t)\ (\mathbf{y}_{\mathrm{j}_k}^{\mathrm{est}}(t))^H \tag{4}$$

be the averaged correlation matrix of $\mathbf{y}_{\mathrm{j}_k}^{\mathrm{est}}(t)$.

Applying the SVD of $\mathbf{R}_k^{\mathrm{est}}$ [14], [15], we obtain

$$\mathbf{R}_k^{\mathrm{est}} = [\mathbf{U}_{\mathrm{s}}\ \mathbf{U}_{\mathrm{n}}] \begin{bmatrix} \mathbf{\Lambda}_{\mathrm{s}} & 0 \\ 0 & \mathbf{\Lambda}_{\mathrm{n}} \end{bmatrix} \begin{bmatrix} \mathbf{U}_{\mathrm{s}}^H \\ \mathbf{U}_{\mathrm{n}}^H \end{bmatrix}, \tag{5}$$

where the SVD is represented by separating signal and noise spaces. Separation of signal and noise spaces can be based on the estimated number of interfering streams, J, which can be obtained via, e.g., the minimum description length (MDL) method [16].

We can then obtain the estimated null space matrix $\hat{\mathbf{Q}}_k \in \mathbb{C}^{(N_k-J)\times N_k}$ as

$$\hat{\mathbf{Q}}_k = \mathbf{U}_{\mathrm{n}}, \tag{6}$$

where $\mathbf{U}_{\mathrm{n}} \in \mathbb{C}^{N_k \times (N_k-J)}$ spans the noise subspace [15] and corresponds to the $N_k - J$ least singular values.

Note that the estimated null space actually is the null space of the received signals, $\mathbf{Q}_k^{\mathrm{sig}}$, and does not necessarily correspond to the null space of the channel matrix $\mathbf{Z}_k$, $\mathbf{Q}_k$. The effectiveness of suppressing interference signals depends on how close $\hat{\mathbf{Q}}_k$ is to $\mathbf{Q}_k$, which is affected by two major factors.

The first factor is the interferers' channel variation over a time period T_b of interest. This factor can be quantified by $T_b F_d$, where F_d is the interference channels' Doppler spread [17]. For a communication system, a larger value of $T_b F_d$ means channel changes rapidly, and hence $\hat{\mathbf{Q}}_k$ needs to be updated more frequently. However, frequently updating $\hat{\mathbf{Q}}_k$ means more overhead for the communication system.

The second factor is the interference signals' correlation, which directly affects the similarity between $\hat{\mathbf{Q}}_k$ and $\mathbf{Q}_k^{\text{sig}}$. When the interfering signals are uncorrelated, $\mathbf{Q}_k = \mathbf{Q}_k^{\text{sig}}$; but the equality does not hold when the interfering signals are correlated. When interfering signals are correlated, we end up with estimating $\mathbf{Q}_k^{\text{sig}}$, which is the null space of the equivalent interfering channel matrices seen by the UE. The estimate $\hat{\mathbf{Q}}_k$ becomes less effective in suppressing interference signals when signal correlation changes. However, only if the correlation remain unchanged, the estimated null space can still suppress most of interfering signals.

Since some important processing after the interference nullification depends on $\mathbf{W}_k(t)$, updating $\mathbf{W}_k(t)$ would require the update of many other variables, including the equivalent channel matrix $\mathbf{H}_k^{\text{eq}}$ and the equalizer. Null space computation involves high-complexity SVD or other similar operations, and updating equalizer typically involves high-complexity matrix inversion. Therefore the complexity will be very high, if conventional approaches are used. A good idea is to update $\hat{\mathbf{Q}}_k$ and $\mathbf{W}_k^H(t)$ separately, and use the null space tracking algorithm as will be detailed next.

D. Null Space Tracking

Many null space tracking algorithms have been proposed in the literature to track and update the signal and/or null spaces from SVD, such as the fast orthogonal Oja (FOOJA) [18], data projection method (DPM) [19], and fast DPM (FDPM) [15]. The FDPM has a low complexity of $\mathcal{O}(N_k(N_k-J))$, a high convergence rate, and excellent numerical stability. Therefore, we select FDPM for null space tracking in our proposed method. A detailed description of the FDPM algorithm can be found in [14], [15].

The SVD is used to acquire the initial $\hat{\mathbf{Q}}_k$ during the initial long silent period, and the FDPM algorithm is applied to track and update $\hat{\mathbf{Q}}_k$ during the zero-pilots and the short interframe silent periods. Hence SVD only needs to be done once per superframe.

It should be noted that the adaptive filter coefficients are updated by using the signal after applying the matrix $(\mathbf{W}_k(t))^H$, while the null space tracking is done by using the signal before applying $(\mathbf{W}_k(t))^H$. The null space tracking cannot be applied to $(\mathbf{W}_k(t))^H\mathbf{y}_k$ as $\mathbf{W}_k(t)$ is not full row-rank and therefore, the tracking will not return an efficient output.

As all the normal signal processing at the receiver is based on signals after applying $(\mathbf{W}_k(t))^H$, channel and equalization coefficients would need to be re-estimated if $\mathbf{W}_k(t)$ is updated directly after null space tracking. Therefore, for convenience we only update $\mathbf{W}_k(t)$ once each frame, although $\hat{\mathbf{Q}}_k$ is updated every zero pilot. This enables tracking and updating $\hat{\mathbf{Q}}_k$ in time, using scattered short zero pilots. But it does not support the usage of long packets, as $\mathbf{W}_k(t)$ is not updated and residual interference could become very large.

Although the channel estimate can be updated readily after updating the null space, it is not easy to update the equalization coefficients. The main reason is that updating the equalization coefficients involves matrix inversion and the complexity is high. This can be seen from the following analysis. Other variables in the adaptive equalizer may also need to be updated.

There exists a multiplicative relationship between the new and current null space matrices:

$$\hat{\mathbf{Q}}_k(t+1) = \hat{\mathbf{Q}}_k(t)\mathbf{G}(t+1), \tag{7}$$

where $\mathbf{G}(t+1)$ is a full rank square matrix of size $(N_k-J)\times(N_k-J)$. Since both $\hat{\mathbf{Q}}_k(t)$ and $\hat{\mathbf{Q}}_k(t+1)$ are submatrices of orthonormal matrices, we can get

$$\mathbf{G}(t+1) = \hat{\mathbf{Q}}_k^H(t)\hat{\mathbf{Q}}_k(t+1). \tag{8}$$

Let $\mathbf{W}_{ak}(t) = \hat{\mathbf{Q}}_k(t)$, and consider a linear equalization matrix $\mathbf{W}_e(t)$. Updating $\mathbf{W}_k(t+1)$ to $\hat{\mathbf{Q}}_k(t+1)$ requires

$$\begin{aligned}\mathbf{W}_e(t)\hat{\mathbf{Q}}_k(t) &= \mathbf{W}_e(t)(\mathbf{G}^H(t+1))^{-1}(\mathbf{G}^H(t+1)\hat{\mathbf{Q}}_k^H(t))\\ &= (\mathbf{W}_e(t)(\mathbf{G}^H(t+1))^{-1})\mathbf{W}_k(t+1),\end{aligned} \tag{9}$$

and $\mathbf{W}_e(t+1) = \mathbf{W}_e(t)(\mathbf{G}^H(t+1))^{-1}$. Thus the linear equalization matrix $\mathbf{W}_e(t)$ needs to be updated by multiplying the current one with an inverse matrix of $\mathbf{G}^H(t+1)$. Unfortunately, there is no fast algorithm to compute $(\mathbf{G}^H(t+1))^{-1}$, and the complexity is $O((N_k-J)^3)$.

An alternative approach to the FDPM tracking is updating the correlation matrix only, by using the signals at the zero pilots, and then conducting an SVD to estimate the null space at the start of each packet. This may have overall lower complexity, depending on the number of total zero pilots. However, simulation results show that the FDPM algorithm achieves better performance.

E. The Complete Algorithm

Algorithm 1 presents the complete methodology. It starts with a silent period, during which the BS does not send any signals. The channel null space is then estimated from the received interference signal, and we obtain the initial $\hat{\mathbf{Q}}_k \in \mathbb{C}^{(N_k-J)\times N_k}$. Based on $\hat{\mathbf{Q}}_k$, we design $\mathbf{W}_k(t)$ by letting $\mathbf{W}_k(t) = \hat{\mathbf{Q}}_k$. Since the interference signals are mostly removed by using $\mathbf{W}_k(t)$, the equivalent channel

$$\mathbf{H}_k^{\text{eq}} = \mathbf{W}_k^H(t)\mathbf{H}_k(t)\mathbf{P}_k$$

can be estimated by using the LTS. Adaptive equalizers as discussed in Section III-B are then applied to decode the data symbols. The equalizer coefficients are updated adaptively using received signals from the data pilots. Each UE can then demodulate all $N_k - J$ spatial streams, and retain the streams for itself only. The FDPM algorithm is applied to update the null space estimate, using the received signals corresponding to the zero pilots. The $\mathbf{W}_k(t)$ is then updated and applied at the start of the next frame.

Algorithm 1 The complete scheme.

```
1: while 1 do
2:     During the silent null space acquisition period, UE estimates Q̂_k.
3:     At the start of each packet, design W_k(t) from Q̂_k and apply it to the received signal.
4:     Synchronize and estimate the equivalent channel H_k^eq using the preamble in packets.
5:     Use one of the adaptive filters in Section III-B to equalize the signal r_k(t). Demodulate the equalized signals for the streams for user k.
6:     Update the null space estimate Q̂_k using the FDPM algorithm with signals received corresponding to the zero pilots;
7:     Update the coefficients of the adaptive equalizer using the data pilot, and apply the updated coefficients for equalization;
8:     Repeat from 3.
9: end while
```

Parameters	Meaning	Values
v	Moving speeds of interferers (km/h)	150 and 20
riceK	Ricean factor in Ricean channels	1 and 4
Tsilence	# samples in the initial silence period	64
Tpilots	# zero pilots in each virtual block	3
segmentLen	Length of each virtual block;	50
corrCoef	Correlation coefficients of signals	various
SNR	Signal-to-noise ratio (dB)	35
μ	Learning rate factor in FDPM	between 0 and 1.

TABLE I: Basic system parameters.

IV. Simulation Results

We provide some simulation results in this section to validate the effectiveness of the proposed scheme. The time-varying channel models for both UE and interferers are simulated using the Jakes model [20]. A single carrier narrowband MIMO system is considered with a bandwidth of 2MHz and central frequency at 447 MHz. Each UE and the BS are assumed to have a uniform linear array of 8 antennas. The BS is communicating with four UE, each having one spatial streams.

We first test the null space tracking algorithm, and then the entire scheme.

A. Tracking Time-varying Null Space

The parameters used in the simulation here are shown in Table I, unless noted otherwise.

We compare the tracking performance for the following methods:

- *PerSample*: FDPM method, updated per zero pilot;
- *Direct-SVD*: Correlation matrix updated across zero pilots, and then SVD is computed and null space updated every segment of zero pilots;
- *Ideal*: Ideal null space derived directly from the channel matrix;
- *perBlock*: FDPM method, but with one iteration per segment of zero pilots. All signals are input together;
- *Initial*: Using the initially estimated null space, without updating.

The tracking performance is evaluated using the normalized residual signal power, which is defined as the ratio between the signal power after and before applying $(\mathbf{W_k(t)})^{\mathbf{H}}$.

In Fig. 3, the tracking results for non-correlated signals are presented, with μ=0.5 and 0.7, respectively. The two subfigures show that the PerSample FDPM achieves the best tracking performance, and the performance with μ=0.7 is slightly better than that with μ=0.5. However, this does not mean that a larger μ always achieves better performance. Actually, we've found that the best values depend on many factors, such as the SNR, the signal correlation, and the channel variation speed. A general rule of thumb is, a larger μ is better for higher SNR and rapid channel variation, and a smaller one is better otherwise. An adaptive learning factor is yet to be investigated. Comparing the two subfigures, we can also see that with u increasing, the performance gap between the perSample and perBlock methods is reduced. Since the perBlock method has a lower complexity, this indicates that using the perBlock method with a larger μ is preferred if a low-complexity implementation is desired.

Fig. 4 presents the tracking performance for signals with varying correlation coefficients. It is shown that the FDPM method can adapt to the change of the correlation well. Comparing the two subfigures, we can see that when the changes of correlation coefficients are small, the adaptation happens quickly, and the performance variation is small. When the changes are large, convergence is slower, particularly when the correlation coefficient decreases to a much smaller one. The performance gap is also large when the variation is large.

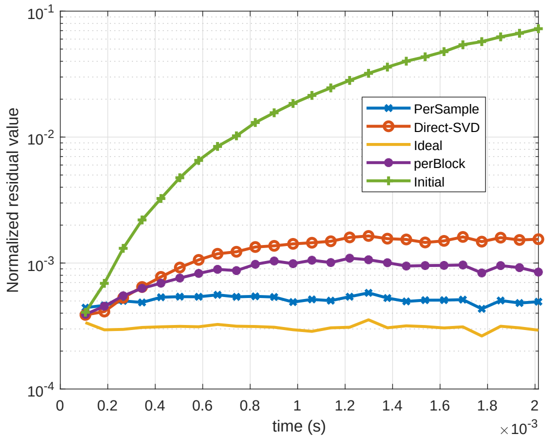
B. Demodulation Performance

We present simulation results for the demodulation performance. The simulated adaptive equalizers are CGE and RLS-FFE, together with a zero-forcing (ZF) equalizer with fixed coefficients for comparison. The initial parameters of all the equalizers are determined using the LTS, and then they are updated using the signals corresponding to the pilots. The basic system parameters are similar to those in Table I, and some additional parameters and revisions are shown in Table II. The lengths of LTS is 32 and the interframe silent period is 10 samples. Correlation coefficient between interfering signals is set as 0.1.

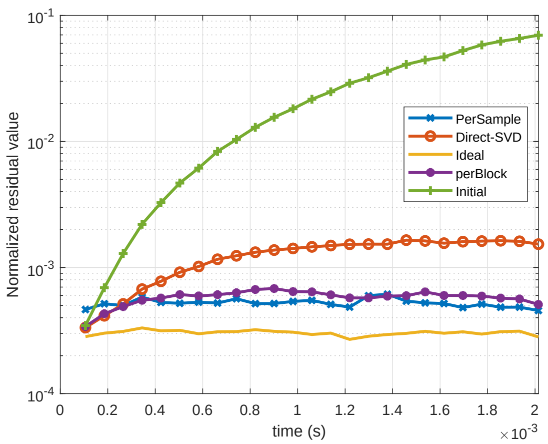
Parameters	Meaning	Values
UE moving speed	Moving speeds of UE (km/h)	[40 80 100 0]
Modulation		16QAM
UE SNR	SNR of UE signals (dB)	25
v	Interferer Moving Speeds (km/h)	[40, 60]
γ	Power ratio between interfering and effective signals	[2,1]
μ	learning factor	0.7
L_p	Length of data pilots	1

TABLE II: Additional system parameters used in simulating demodulation performance.

We first test the performance of the equalization methods on handling time-varying UE channels, without interfering

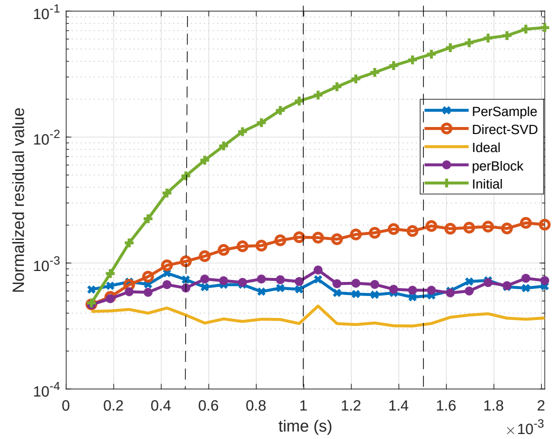


(a) μ=0.5.

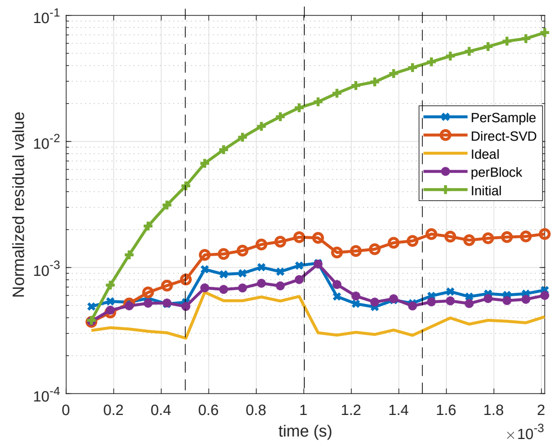


(b) μ=0.7.

Fig. 3: Channel tracking results using FDPM for uncorrelated signals.



(a) Correlation coefficients [0.6, 0.3, 0.0, 0.4].



(b) Correlation coefficients [0.1, 0.9, 0.0, 0.45].

Fig. 4: Channel tracking results using FDPM for signals with varying correlation coefficients. Signals with each correlation coefficient last the same period of 0.5035 ms, starting from 0ms. Here μ=0.7.

signals. The data payload length is set as 1500 samples, to clearly demonstrate the capabilities of these methods. The mean BER, averaged over all UE, is shown in the first row in Table III.

The simulation results show that the adaptive equalizers all achieve better performance than ZF. The CGE achieves a balance between performance and complexity, and is determined as the best option. The results also show that the proposed adaptive equalizers are effective in dealing with time-varying UE channels, but are not very effective in dealing with the varying null space of the interference channels, as explained in Section I.

We then simulate the cases with static and moving interferers, and show the mean BER results in rows 2 to 4 in Table III. In each superframe, 5 frames are transmitted, with an interframe interval of 10 samples. We compare the cases including no interference, static interferers (all tracking is still enabled), mobile interferers without any null space tracking, mobile interferers with only interframe null space tracking, and mobile interferers with both intra-frame and interframe null space tracking. The data payload length in each packet is reduced to 500 samples, to allow the update of $\mathbf{W_k}(\mathbf{t})$ in time. The PerSample FDPM tracking is applied, when the estimated interferers are present.

In Fig. 5, we present the BER performance for the CGE with moving interferers. The three groups of curves clearly show the significant improvement achieved by using tracking, in particular, both intra-frame and inter-frame tracking. They also clearly demonstrate that the adaptive equalizer itself cannot mitigate the interference due to changing interfering channels and channel null spaces.

From the BER results in Table III, we make the following observations:

- Both adaptive equalizers are effective in handling time-varying UE channels, but not very effective for time-varying null space;
- UE channel variation has smaller impact on system BER, compared to variation of interfering channels;
- For short packets or small accumulated variation within a packet, adaptive equalizers do not show any advantages.

Scenarios	ZF	CGE	RLS-FFE
No Interferer (data payload length 1500)	5.6267e-04	1.4956e-04	1.5400e-04
With fixed Interferer (with all tracking)	0.0018	0.0020	0.0021
With mobile Interferer (without any tracking)	0.1079	0.0427	0.0181
With mobile Interferer (without intra-packet tracking)	0.0172	0.0100	0.0076
With mobile Interferer (with all tracking)	0.0088	0.008	0.0064

TABLE III: BER results for various equalizers.

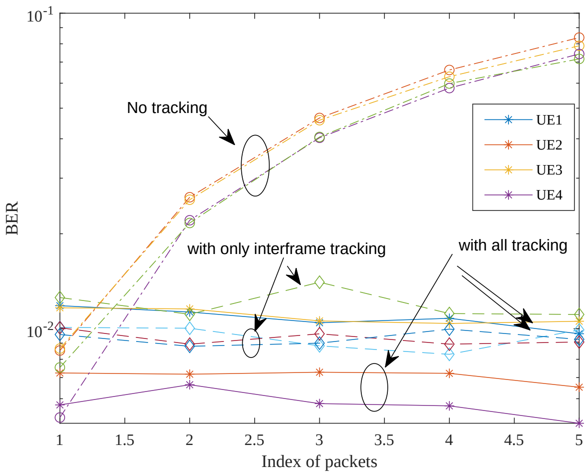


Fig. 5: BER performance of the CGE for mobile interferers. Five packets are continuously transmitted in one superframe. The dash-dot curves with circle marks, dash-curves with diamond marks, and solid curves with star marks are for the cases without any tracking, with only interframe tracking and with all tracking, respectively.

V. Conclusion

In this paper, we presented a scheme to overcome time-varying user and interfering channels. We developed different techniques to deal with these two types of channel variations. A new improved superframe structure is proposed to allow channel and null space tracking. A null space tracking algorithm, FDPM, is tested for updating the null space matrix, which is then used to update the equalizer at the start of each frame. Several adaptive filters, including CGE, RLS-FFE, and DFE, are improved and tested. Simulation results show the effectiveness of the proposed scheme.

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