Pulsed and narrowband mixed interference mitigation technique for single antenna GNSS receivers

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Abstract: Most previous works focus on single type of interference mitigation and simplified combination of these existed methods leads to high disabled probabilities of single antenna Global Navigation Satellite System (GNSS) receivers under mixed interference scenarios due to the interaction of different types of interferers. In this paper, depending on the assumption that pulsed interference repetition period is known, we introduce a segmentation method which will guarantee the success of narrowband interference (NBI) power spectrum density (PSD) estimation by minimum operation in mixed interference. Then NBI and pulsed interference can be mitigated, subsequently. The effectiveness is validated by numerical simulation results.

Keywords: anti-jamming receiver, Global Navigation Satellite System (GNSS), interference mitigation, pulse blanking (PB)

Classification: Navigation, Guidance and Control Systems

References


1 Introduction

Periodic-pulsed interference (PPI) and narrowband interference (NBI) are two types of detrimental interference for Global Navigation Satellite System (GNSS) receivers [1] and the immunity of single antenna GNSS receivers against PPI and NBI can be greatly enhanced by the corresponding mitigation techniques [2, 3, 4]. The typically PPI sources for GNSS receivers are transmitted from DME/TACAN, primary L-band radars, AEW&C L-band radars and TADIL-J/Link-16 [5]. NBIs could originate from amplitude modulation, frequency modulation stations transmitters harmonics or intentional continuous wave (CW) jammers, etc. [1]. Antenna arrays provide an effective way to mitigate mixed interference [6] but are often quite expensive, computationally very demanding and have large size which make the arrays can not be used in every receiver [7]. Besides, it is difficult to combat the mixed interference effectively by simple combination with these conventional mitigation techniques for single antenna GNSS receivers as shown in Section 4 and surprisingly to the best of our knowledge, the mitigation for mixture of PPI and NBI has not received much attention.

For simplicity, only PPIs originating from the primary L-band radars and NBIs whose bandwidth are lower than 10% of the bandwidth of the desired signal [7] are considered in this paper. The results discussed in the following section for primary L-band radars is easily extended to other cases which is out of the scope of this paper. For primary L-band radars which can be deemed as low duty cycle (DC) PPIs, pulse blanking (PB) [2] is an effective mitigation technique due to its simplicity and effectiveness. Noting that transformed-domain techniques [8, 9] can be used to suppress high DC PPIs instead of PB.

2 Signal model

The input samples denoted as $x(n)$ with sampling frequency $f_s = 1/T_s$, can be expressed with

$$x(n) = s(n) + q(n) + p(n) + \eta(n)$$  \hspace{1cm} (1)

where $s(n)$ denotes the desired GNSS signal, $q(n)$ is the stationary NBI, $p(n)$ is the PPI, and $\eta(n)$ denotes the complex Gaussian white noise with zero mean and
variance $\sigma^2_n$, i.e., $\eta(n) \sim \mathcal{C}\mathcal{N}(0, \sigma^2_n)$ with PSD $S^\eta(f) = \sigma^2_n / f_s$, $f \in [-1/2, 1/2)$. In this paper, we assume that all the components in (1) are statistically uncorrelated with each other. Generally, $s(n)$ with PSD $S^s(f)$ and Binary phase shift keying (BPSK) modulation in (1) can be defined as $s(n) = \sqrt{C}d(n)c(n) \exp(j2\pi f_d n + \phi_0)$, where $C$ is the power, $d(n) \in \{ \pm 1 \}$ represents the data modulation, $c(n) \in \{ \pm 1 \}$ is the spreading code with chipping rate $R_s$, $j = \sqrt{-1}$ is the imaginary unit, $\phi_0$ is the initial carrier phase. For the sake of clarity, the data modulation term is omitted in the following analyses. This result discussed in the following section based on BPSK signal is easily extended to Binary Offset Carrier (BOC) cases.

The NBI signal $q(n)$ is modeled as a block spectrum $S^q(f)$ with bandwidth $\Delta f \in (0, 1)$. It is written as

$$S^q(f) = \begin{cases} P_1 / \Delta f, & |f - f_q| \leq \Delta f / 2 \\ 0, & \text{otherwise} \end{cases}$$

(2)

where $P_1, f_q$ denote the NBI power and center frequency, respectively. This means that $q(n)$ can be realized by passing a complex white Gaussian process through a band-limited filter and we will generate $q(n)$ by this mean in Section IV. When the narrowband interference is centered on a local maximum in the desired signal spectrum, it causes a local minimum in the effective carrier-to-noise ratio ($C/N_0$) [1], thus we assume that $f_q = f_d$ hereinafter. The interference-to-noise (INR) of $q(n)$, denoted as INR, can be defined as $INR = P_1 / \sigma^2_n$, and we define

$$S^{NBI}(f) = S^q(f) + S^j(f) + S^\eta(f)$$

(3)

as the NBI PSD without PPI disturbance. The $p(n)$ in (1), can assume different forms depending on the type of interference source and can, in general, be represented as

$$p(n) = i_c(nT_s) \sum_{i=0}^{\infty} p_0(nT_s - i_1T_p - T_0)$$

(4)

where $T_p$ is the pulse period, $T_0$ accounts for an arbitrary time origin, $i_c(n)$ is a continuous component and $p_0$ is a function defined as

$$p_0(t) = \begin{cases} 1, & 0 \leq t \leq \rho T_p \\ 0, & \text{otherwise} \end{cases}$$

(5)

where $T_p$ is the repetition period, $\rho$ denotes DC, and $T_0$ accounts for an arbitrary time origin. In this paper, $i_c(nT_s)$ is assumed to be a zero mean complex Gaussian noise interference with power $P_2$, which has a bandwidth equal to useful GNSS signals. Thus the INR of $p(n)$, denoted as INR, can be defined as $INR = P_2 / \sigma^2_n$.

If $S^{NBI}$ can be estimated accurately, the pulsed and narrowband mixed interference can be suppressed easily. However, it is difficult to estimate the NBI PSD with traditional consecutive blocks method due to the following reasons. The presence of PPI will make the NBI and pulsed interference blanking weights biased. Even if we know the pulse period and duty cycle, it is still difficult to estimate $S^{NBI}_x$ due to the uncertainty of $T_0$ in (4). In addition, the relation between $P_1$ and $P_2$ is not assumed. All mentioned above reasons will make the simplified
combinations of convention interference mitigation techniques failed under the mixed interference scenarios. The proposed technique will be illustrated in Section 3, which can estimate accurately the NBI-only PSD from the mixed interference.

As defined in (2), the \( q(n) \) is assumed to be stationary and has a box spectrum of bandwidth \( \Delta f \). Thus, the ideal frequency- and time-domain blanking functions, corresponding \( q(n) \) and \( p(n) \), can be written as

\[
F_b(f) = \begin{cases} 
0, & |f - f_b| \leq \frac{\Delta f}{2} \\
1, & \text{otherwise}
\end{cases} 
\]

(6)

\[
T_b(n) = 1 - \sum_{l=0}^{\infty} p_0(n - l T_p - T_0)
\]

(7)

Based on interference-free signal \( x_0(n) = s(n) + \eta(n) \), because it is needless to show any consideration for the effect of interference leakage after mitigation in reality. Based on (6) and (7), the ideal mitigation outputs which are used to evaluate interference mitigation technique performance, can be written as

\[
y(n) = \text{IDFT}\{\text{DFT}\{x_0\} \times F_b(n) \times T_b(n)\}
\]

(8)

where \( y(n) \) is corresponding to the presence of \( q(n) + p(n) \) scenarios as shown in Section 4.

### 3 Proposed technique

When the pulsed and narrowband mixed interference is present, all the samples are nearly contaminated by NBI but partial by PPI per pulse period. The key idea of the proposed technique is to estimate the NBI PSD using different blocks per pulse period in which at least one block is not corrupted by the pulsed interference. We assume that the samples of a pulse period are grouped into \( L \) blocks with equal block size and the \( l \)th block vector of \( m \)th pulse period is give by

\[
x_{m,l} = [x(0 + A_l + B_m), \cdots, x(N - 1 + A_l + B_m)]^T
\]

(9)

where \( m = 0, 1, \cdots; l = 0, 1, \cdots, L - 1 \), \( \lceil \cdot \rceil \) rounds the element to the nearest integers toward minus infinity and \( A_l = \lfloor f_s T_p / L \rfloor, B_m = \lfloor m f_s T_p \rfloor \).

Based on the idea of the proposed technique, it is significantly to decide how many blocks being segmented per pulse period. Obviously, at least a whole block should not be contaminated by the PPI for \( m \)th pulse period. The \( m \)th pulse period samples is segmented into \( L \) blocks with block size \( \lfloor f_s T_p / L \rfloor \). Based on the Pigeon Hole principle, if the following expression holds:

\[
f_s (1 - \rho) T_p \geq 2 \times f_s T_p / L
\]

(10)
at least one noncorrupted block by the pulsed interference can be guaranteed. Considering \( L \) as a positive integer, (10) can be rewritten as \( L \geq \lceil 2 / (1 - \rho) \rceil \), where \( \lceil \cdot \rceil \) rounds the element to the nearest integers toward infinity. We can choose a data frame with \( N \) continuous samples for every block for PSD estimation and \( L \) averaged PSDs can be computed over \( M \) pulse periods, separately. For the case of \( f_s = 4.092 \text{ MHz} \), \( T_{p_{\text{min}}} = 1 \text{ ms} \), \( T_{p_{\text{max}}} = 2.5 \text{ ms} \) and \( \rho_{\text{max}} = 10\% \) for primary L-band radars [5], we can set \( N = 1024 \) and \( L = 3 \), for example.
Passing through windowing function $w$ of length $N$ and an $N$-point FFT transform ($N$ is assumed an even number in the letter), the $x_{m,l}$ yields the Fourier coefficients records $X_{m,l}(k) = \frac{1}{\sqrt{N}} \sum_{i=0}^{N-1} w(i)x_{m,l}(i)\exp(-j2\pi ik/N)$, $k = -N/2, \ldots, N/2 - 1$. We denote the squared magnitude of $X_{m,l}(k)$ by $S_{m,l}(k)$, i.e., $S_{m,l}(k) = |X_{m,l}(k)|^2$. The $k$th averaged squared magnitude of Fourier coefficient record for all $l$th blocks, denoted as $\hat{S}_{m,l,M}(k)$, can be written as $\hat{S}_{m,l,M}(k) = 1/M \sum_{m=0}^{M-1} S_{m,l}(k)$. We can choose the minimum value under proper value of $M$ among $L$ averaged PSD blocks at $k$th frequency bin, i.e.

$$\min_{l} \{ \hat{S}_{m,l,M}(k) \}$$

(11)

for windowed NBI PSD estimation due to

$$\min_{l} \left\{ \lim_{M \to \infty} E(\hat{S}_{m,l,M}(k)) \right\} = \sigma_w^2 S_x^{\text{NBI}}(k/N)$$

(12)

where $\sigma_w^2 = \sum_{i=0}^{N-1} w^2(i)$ is the energy of the window function $w$.

### 4 Numerical results

The effectiveness of proposed technique are evaluated by means of Monte Carlo simulations. The sampling frequency is fixed at 4.092 MHz. A GNSS signal $s(n)$, with signal level of $C/N_0 = 40$ dB-Hz, $R_c = 1.023$ MHz, code length 1023 and $f_o = 0$ rad, is selected. The $q(n)$, with bandwidth of $\Delta f = 0.05$, and $p(n)$ with maximum fixed DC $\rho = 10\%$ and $T_p = 1.7$ ms \(^1\) which is selected between 1 ms and 2.5 ms for L-band radars, are considered. The arbitrary time origin $T_0$ is drawn uniformly taken from the interval $[0, T_p]$ in each simulation run. The sum of INR$_1$ and INR$_2$ is fixed approximatively at 23 dB with different INR$_1$/INR$_2 = \{-10, 0, 10\}$ dB in order to maintain the NBI and PPI strong enough. In all simulation scenarios, $N = 1024$, $L = 4$ and $M = 50$ are chosen, respectively. A Hamming window function for the 50% overlap-and-add approach is used. The scaling factors for NBI and PPI mitigation are set to 4.6 and 5, respectively, which need further optimal investigation. We employ $10^5$ correlation values to obtain each point of the ROC curves with a correlation value consisting of coherent integration over 1 ms duration and a noncoherent accumulation. The synchronization parameters estimations are set as the true values to show the performance of the proposed technique without signal synchronization errors. ‘Ideal mitigation’ curve is obtained based on (8) and ‘Conventional’ cases have been obtained by cascading NBI and PPI mitigation techniques.

As depicted in Fig. 1, the proposed technique have achieved better ROC performance compared with conventional method against strong mixed interference. When the ratio changes between INR$_1$ and INR$_2$, the ROC performance of the conventional one fluctuates greatly due to time-varying nature of pulsed interference while the proposed technique presents a robustness to it. Specially, when the ratio equal to $-10$ dB which means that the pulse interference power is ten times of the NBI, the conventional method is failed to suppress the mixed interferences while the proposed technique gives remarkably performance improvements. The

\(^1\) The ROC comparison results of other NBI bandwidths and PPI periods are omitted due to having similar results.
slight degression for proposed technique compared with the ideal mitigation ROC curves for different INR combinations are due to NBI and PPI blanking ratios increasing and interference leakages under strong interference scenarios.

5 Conclusion

In this paper, we proposed a pulsed and narrowband mixed interference mitigation technique for single antenna GNSS receivers. We utilized the segmenting and minimizing operations to estimate the NBI PSD and NBI mitigation follows. Then the residual strong PPI can be suppressed easily. Simulation results show that the proposed technique can suppress the mixed interference effectively while withholding a performance very close to ideal mitigation for strong mixed interference. The reason for achieved performance comes at the cost of a prior knowledge of pulse repetition period and the stationary assumption of NBI. Future investigations will be focused on the no priori information about the pulsed interference period scenarios.

Fig. 1. ROC curve comparisons for mixed interference scenarios with different INR combinations
Perceptual-based compressed video sensing

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Abstract: The recently introduced compressed sensing (CS) theory can, potentially, simplify the acquisition process of resource-limited devices by taking advantage of signal sparsity. This paper proposes a perceptual-based compressed video sensing (CVS) strategy that benefits from the human visual perception properties. Two frameworks are proposed, namely, Intra-perc-CVS and Inter-perc-CVS. In both frameworks, an efficient perceptual-based weighting strategy is applied for acquisition and recovery. In the Intra-perc-CVS scheme, video frames are acquired and recovered separately, while in the Inter-perc-CVS scheme, the frames are recovered jointly to further exploit inter-frame correlation. The proposed perceptual-based frameworks show remarkable performance improvement over the standard CVS.

Keywords: compressed sensing, video coding, perceptual weighting

Classification: Multimedia Systems for Communications

References

1 Introduction

Compressed sensing (CS) [1] is an emerging signal processing theory that enables direct acquisition of signals that exhibit sparsity or compressibility in some orthonormal basis $\mathbf{\Psi}$, with much lower sampling rate than the traditional Nyquist rate. CS has great potential in image/video coding applications for its low complexity e.g. [2, 3]. Standard video coding techniques rely on several properties to improve the compression efficiency. Most notable of these properties is the discriminative perception of the human eye to different frequencies. However, legacy video coding technology relies on high-complexity encoder in transmitting device that serves millions of low-complexity decoders in receiving devices. This is the opposite objective of the CS technology that targets the widely spread cheap multimedia devices such as multimedia sensors. In cheap acquisition devices, the target is simplifying the acquisition/encoding and moving most of the computational load to the receiver side. Nevertheless, the concept of making use of the perceptual properties of the human eye can be applied to the CS operation. In this paper, we propose compressed video sensing (CVS) schemes, for digital communication, in which an efficient static perceptual-based weighting strategy is applied on the frequency components of the video frames.

2 Background and related work

For a signal $\mathbf{x} \in \mathbb{R}^{N \times 1}$ that can be sparsely or compressibly represented as $\mathbf{\theta} \in \mathbb{R}^{N \times 1}$ through a sparsifying transformation $\mathbf{\Psi} \in \mathbb{R}^{N \times N}$ i.e. $\mathbf{x} = \mathbf{\Psi} \mathbf{\theta}$, CS theory assumes acquiring $M \ll N$ linear samples $\mathbf{y} = \mathbf{\Phi} \mathbf{x} \in \mathbb{R}^{M \times 1}$, where $\mathbf{\Phi} \in \mathbb{R}^{M \times N}$ is the measurement matrix which should be incoherent with $\mathbf{\Psi}$, where $R_{\text{mr}} = M/N$ can be defined as the measurement rate. In addition, the sensing matrix $\mathbf{A} = \mathbf{\Phi} \mathbf{\Psi} \in \mathbb{R}^{M \times N}$ should satisfy restricted isometry property (RIP) [1, 4]. Random basis represents a good selection for measurement matrices because it satisfies incoherence and RIP conditions with any fixed orthonormal basis [4]. Under these conditions, stable and accurate recovery can be achieved via $l_1$-min problem defined below [4]:

where \( \theta^* \) is the reconstructed sparse representation and \( \epsilon \geq 0 \) is a small tolerance. Then, the recovered signal can be obtained as \( x^* = \Psi \theta^* \).

If prior information about the signal is available, the performance of the CS can be improved. Authors in [5] proposed an adaptive CVS system that focuses the coding process on an estimated support derived from previously reconstructed frames through feedback from the decoder/receiver to the encoder/transmitter. In that system, the accuracy of support estimate depends mainly on the quality of the previously reconstructed frames. In contrary to [5], our proposed weighting strategy depends on fixed perceptual-based support estimate and does not require feedback.

Another property widely used in legacy video coding standards is the temporal correlation among consecutive frames. Integrating CS with the recently introduced distributed video coding (DVC) theory [6] enables exploiting inter-frame correlations using simple intra-encoder and joint inter-decoder. Recently, residual-based recovery has proved its efficiency in video coding [7, 8]. In essence, due to the high correlation between successive frames, the sparsity of the residual frames is higher than that of the full frames. We make use of this property by proposing another CVS framework that takes both the perceptual properties and the inter-frame correlation into account.

3 Proposed perceptual-based compressed video sensing

In this paper, two perceptual-based frameworks are proposed, namely, Intra-perc-CVS and Inter-perc-CVS. In the former framework, the frames are intra-encoded/intra-decoded. On the other hand, in the second framework, the frames are intra-encoded but jointly inter-decoded, utilizing residual-based recovery, to exploit inter-frame correlation while keeping the encoder as simple as possible.

3.1 Intra perceptual-based CVS framework (Intra-perc-CVS)

The processing chain of this framework is summarized in Fig. 1a. In this scheme, the frames are acquired and recovered separately. The standard CS measurement matrix and recovery algorithm are modified such that the measurements and recovery are focused on the most perceptually pronounced low-frequency coefficients. The proposed strategy is related to [5], but with static weighting strategy that exploits the predefined locations of the low-frequency discrete cosine transform (DCT) coefficients.

Let \( \hat{T} \subset \{1, 2, \ldots, N\} \) represent the visual support estimate that contains the indices of the low-frequency DCT coefficients in zig-zag scanning order, and \( \hat{T}^c \) is its complement. For the sensing operation, a weighting vector \( \mathbf{w} = [w_1, \ldots, w_i, \ldots, w_N]^T \in \mathbb{R}^{N \times 1} \) and a weighting matrix \( \mathbf{W} \in \mathbb{R}^{N \times N} \) are defined, such that:

\[
 w_i = \begin{cases} 
 1, & i \in \hat{T} \\
 \omega, & i \in \hat{T}^c 
\end{cases}
\]

where \( 0 \leq \omega \leq 1 \), and,
The perceptually modified measurement matrix is defined as:

\[ \tilde{\Phi} = \Phi S, \tag{4} \]

where \( S \) is the modifying matrix defined as:

\[ S = \Psi W \Psi^T \tag{5} \]

The new measurement vector can be represented as:

\[ \tilde{y} = \tilde{\Phi} x = \Phi \Psi \tilde{\theta} \tag{6} \]

This can be considered as if we apply the standard measurement matrix \( \Phi \) to a new signal for which the sparse representation is weighted as: \( \tilde{\theta} = W \theta \).

At the receiver side, the recovery is done through weighted \( l_1 \)-min problem defined as:

\[ \tilde{\theta}^* = \arg \min_{\tilde{\theta} \in \mathbb{R}^{N \times 1}} \| \tilde{\theta} \|_1, \tilde{w} \quad s.t. \quad \| \tilde{y} - \Lambda \tilde{\theta} \|_2 \leq \epsilon \tag{7} \]

where \( \tilde{\theta}^* \) is the reconstructed weighted sparse representation, \( \| \tilde{\theta} \|_1, \tilde{w} = \sum_{i=1}^{N} \tilde{w}_i |\tilde{\theta}_i| \), and \( \tilde{w} = [\tilde{w}_1, \ldots, \tilde{w}_i, \ldots, \tilde{w}_N]^T \in \mathbb{R}^{N \times 1} \) is the weighting vector defined for the recovery, such that:

\[ \tilde{w}_i = \begin{cases} \omega, & i \in \tilde{T} \\ 1, & i \in \tilde{T}^c \end{cases} \tag{8} \]

This weighting strategy forces the recovery algorithm to focus on the coefficients related to \( \tilde{T} \). The optimal values of support estimate size \( |\tilde{T}| \) and weight factor \( \omega \) are determined empirically as \( |\tilde{T}| = 0.85M \) and \( \omega = 0.1 \) [9]. The reconstructed signal can be obtained as \( \tilde{x}^* = \Psi \tilde{\theta}^* \).

**Fig. 1.** Block diagram of the proposed perceptual-based CVS frameworks.
3.2 Inter perceptual-based CVS framework (Inter-perc-CVS)

In this scheme, each video sequence is bundled into a number of groups of pictures (GOPS), where each consists of one key-frame and number of non-key frames. Key-frames are acquired with a higher measurement rate \( R_{mrk} \) than that of the non-key frames \( R_{mrnk} \), because non-key frames are to benefit from joint decoding exploiting inter-frame correlation.

At the transmitter, each frame is acquired separately using perceptual-based CS defined in Sect. 3.1. At the receiver, key-frames are decoded separately using perceptual-based recovery defined in Sect. 3.1, following the block diagram in Fig. 1a. Non-key frames are decoded jointly using residual-based recovery as shown in Fig. 1b, where the residual is calculated in the measurement domain.

Let \( x_p \) represent the predicted non-key frame generated from the previously reconstructed neighboring key-frames. Simple interpolation is used in this paper to generate \( x_p \) as:

\[
x_p = \frac{x_{kprv}^* + x_{k nxt}^*}{2},
\]

where \( x_{kprv}^* \) and \( x_{k nxt}^* \) are the previous and next neighbor reconstructed key-frames to the current non-key frame, respectively. We propose to acquire similar perceptual-based measurement vector as for non-key frame from its predicted frame as:

\[
\tilde{y}_p = \tilde{\Phi}_{nk} x_p,
\]

where \( \tilde{\Phi}_{nk} \in \mathbb{R}^{M_{nk} \times N} \) is the perceptual measurement matrix for the non-key frame. \( M_{nk} \) is the number of measurements for the non-key frame. Then, the residual measurement vector:

\[
\tilde{y}_r = \tilde{y}_{nk} - \tilde{y}_p,
\]

is utilized to recover the residual frame \( x_r \) using perceptual weighted recovery as in Eq. (7) but replacing the full frames with their corresponding residual frames as:

\[
\tilde{\Theta}_r^* = \arg\min_{\Theta \in \mathbb{R}^{N \times N}} \| \Theta \|_1 \text{s.t. } \| \tilde{y}_r - A\tilde{\Theta} \|_2 \leq \epsilon
\]

where \( \tilde{\Theta}_r^* \) is the reconstructed residual weighted sparse representation. The optimal values of \( |\tilde{T}| \) and \( \omega \) for non-key frames are determined empirically as \( |\tilde{T}| = 0.85M_{nk} \) and \( \omega = 0 \). Then, the reconstructed residual frame can be obtained as \( x_r^* = \Psi \tilde{\Theta}_r^* \) and the reconstructed non-key frame can be obtained as:

\[
x_{nk}^* = x_p + x_r^*,
\]

4 Simulation results

For the simulation, we use the computationally efficient Scrambled Block Hadamard Ensemble (SBHE) as measurement matrix \( \Phi \) [10], 2D-DCT as sparsity basis, and Gradient Projection for Sparse Reconstruction (GPSR) in [11] as recovery algorithm. For Inter-perc-CVS, we use GOP size = 2 and \( R_{mrk} > R_{mrnk} \), e.g., for the average \( R_{mr} = 0.5 \), \( R_{mrk} = 0.7 \) and \( R_{mrnk} = 0.3 \) are selected. The proposed frameworks are tested on different publically available test video sequences. We consider here, “Foreman” as a high-motion video sequence and “News” as a low-motion video sequence [12] (100 frames each, CIF resolution 288×352, Y component).
The proposed frameworks are compared with the standard CVS (Std-CVS) and the adaptive CVS [5] (AdaptCVS).

Fig. 2 shows the peak signal-to-noise power ratio (PSNR) with different average measurement rates for different systems.

\[ PSNR = 10 \log_{10} \frac{\text{MAX}_I^2}{MSE} \]  

where \( \text{MAX}_I = 255 \) is the maximum possible pixel value of 8 bits image, and \( MSE \) is the mean square error between the original signal and the recovered signal. It can be seen that, perceptual-based frameworks give remarkable improvement over Std-CVS and AdaptCVS. Moreover, Inter-perc-CVS can achieve remarkable gain over Intra-perc-CVS due to the efficient residual-based recovery, especially for low-motion videos as can be seen from Fig. 2a for “New” sequence. This remarkable performance for low-motion sequence is due to the fact that the predicted version of the non-key frame is more accurate in the case of low-motion videos than the case of high-motion videos.

Fig. 3 shows the reconstruction time for different frameworks. For fair comparison, we assume, for all frameworks, that, the transmitter and the receiver are back to back, i.e. the decoder starts the recovery process immediately. It can be seen, for all CS-based systems, that, the higher the measurement rate the lower the reconstruction time. The results also demonstrate that, Std-CVS and AdaptCVS consume the lowest reconstruction time with superior performance for AdaptCVS
at lower measurement rates. Intra-perc-CVS consumes the largest reconstruction time. The main reason is the smaller weight factor $\omega = 0.1$ for Intra-perc-CVS compared to $\omega = 0.5$ for AdaptCVS [5]. However, Inter-perc-CVS consumes comparable reconstruction time with Std-CVS and AdaptCVS due to focusing recovery of non-key frames on fewer number of coefficients compared to Intra-perc-CVS.

5 Conclusion and future work

In this paper, we propose two perceptual-based CVS frameworks. The proposed frameworks proved remarkable performance gain in terms of PSNR over the standard CVS frameworks. Moreover, the Inter-perc-CVS proved remarkable improvements over the Intra-perc-CVS both in the quality and the reconstruction time. For future work, we aim to extend our work to take into consideration the quantization effects on perceptual-based CVS.
Fast demodulation method for passive MIMO communication by using beam-forming at receiver

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Abstract: In this letter, we propose the demodulation method to improve the complexity of demodulation in passive MIMO (Multiple-Input Multiple-Output) scheme. This scheme uses the multiple antennas at both reader and RFID (Radio Frequency Identification) tag to increase the data-rate, but the complexity of MLD (Maximum Likelihood Detection), which is used as demodulation algorithm, increases exponentially with the number of antennas. The proposed method divides tag antennas into two groups that do not interfere each other by decoupling tag antenna groups using 180-degree hybrids at tag side and beam-forming at receiver side. Individual demodulation for each group improves the complexity of MLD significantly. Simulation results show the proposed method can reduce the complexity of MLD with degrading slight BER (Bit-Error-Rate) performance. The results reveal the proposed method is effective in reducing demodulation complexity of passive MIMO transmission even when the number of tag antennas is increased.

Keywords: MIMO, RFID, load modulation, beam-forming, MLD

Classification: Antennas and Propagation

References


1 Introduction

RFID (Radio Frequency Identification) is the technology to identify human and materials by using radio frequency tags [1]. For example, it is used electronic money, travel card, employee ID card, and so on [2]. Especially, passive RFID gets a lot of attention in the RFID scheme, because passive RFID tags do not need the power supply [3]. Due to its convenience, the passive RFID is expected to be used for the logistic management, and so on. However, passive RFID has a problem that the transmission speed between reader and tags is not sufficiently high if they need to transfer a large data, such as photo images, video, and so on [4].

To increase the data rate in passive RFID communication, the passive MIMO (Multiple-Input Multiple-Output) technique has been proposed [4, 5]. Passive MIMO uses the multiple antennas at both reader and tag sides, and also uses multi-level load modulation by variable impedance. The tag data can be parallelly transmitted to the reader antennas. At the reader side, the multiple load modulated signals are observed, and they are decoded by using MLD (Maximum Likelihood Detection) [6]. In this scheme, parallel data transmission is realized without extending frequency resources. When mutual coupling at the tag side is existed, the load modulated signals are modulated again by other tag. Therefore, the other demodulation scheme, such as eigenmode beam-forming, cannot realize the parallel data transmission. MLD can decode the multiple signals from the tag antennas even in this case. But, the complexity of MLD exponentially increases with the number of antennas.

In this letter, the demodulation method that significantly decreases the complexity of MLD by introducing analog signal processing is proposed. The analog signal processing at the tag side is realized by using 180-degree hybrid and this decouples the mutual coupling between two antenna groups that are configured symmetrically to each other [7, 8]. This scheme enables the reader receiver to demodulate the signal sets corresponding two antenna groups individually by using the digital beam-forming. Therefore, the complexity of MLD is significantly reduced since the total number of the signals for demodulation is reduced. The effectiveness of proposed method is evaluated numerically.
2 Group demodulation method by using beam-forming

Fig. 1 shows the proposed system model of group demodulation method. $H_{RT}$ represents the propagation channel from reader-transmitter (Tx) to reader-receiver (Rx), and $H_{PT}, H_{RP}$ are respectively represented the propagation channel from Tx to Px and from tags (Px) to Rx. $S_{PP}$ is the scattering matrix representing the S-parameter of tag antenna. $S'_{PP}$ is the scattering matrix including 180-degree hybrids. 180-degree hybrids can decouple two groups of the tag antennas, when the structure is symmetric and the number of antennas is even [7, 8]. In case of configuring tag antennas symmetrically, $S'_{PP}$ is represented as

$$S'_{PP} = \begin{pmatrix} S_{PP_{1\ldots M/2}} & O \\ O & S_{PP_{M/2+1\ldots M}} \end{pmatrix}$$

(1)

where $S_{PP_{1\ldots M/2}}$ is the scattering matrix representing the S-parameter which is composed of tag1, ..., M/2, and $S_{PP_{M/2+1\ldots M}}$ is composed of tagM/2 + 1, ..., M. $O$ is zero matrix. From (1), two antenna groups are isolated completely. Reader can discretely demodulate the signal sets corresponding to two groups by beam-forming. Since the number of the antennas in each group can be reduced by half, the complexity of MLD is reduced significantly compared with that of the conventional method.

Fig. 2(a) shows an estimation method of the channel via Px, $H_{k}$. $M_P$ is the number of tag antennas, $M_R$ is the number of receiver antennas. Proposed method needs the channel via Px for beam-forming at reader, but Rx can only observe the sum of the direct signal and reflected signal via Px. Therefore, the reader needs to estimate the channel from Px to Rx by excluding the direct path. Fig. 2(a) shows the way to estimate the direct path channel. Reference impedance terminates each tag antennas to suppress the reflection from tag, that is, the reflection coefficient is 0. Therefore, only the direct path channel, $H_{RT}$, can be observed at the reader. Fig. 2(b) shows estimation of the sum of direct and reflected path channel. In order to observe the channel components, one of the reflection coefficients of the tag antenna terminations is set to 1 (open) and the rest of the other terminations are set.
to 0. $H_k$ is the reflected path channel when the termination condition of the tags is represented by $\Gamma_k$, which is given as

$$\Gamma_k = \text{diag}(0 \ldots 0, \gamma_{\text{open } k}, 0 \ldots 0)$$  \hspace{1cm} (2)

where $\gamma_{\text{open } k}$ is the reflection coefficient when the load impedance of $k$-th port is opened. The sum of the direct and reflected channels, $H$, which is observed at receiver, is represented by

$$H = H_{RT} + H_{RP}(S_{PP}^{-1} - \Gamma_k^{-1})^{-1}H_{PT}$$  \hspace{1cm} (3)

where $H_{PT}$, $H_{RP}$ is the channels from Tx to Px and from Px to Rx, respectively. Since $H_{RT}$ has been estimated, $H_k$ via tag$k$ can be calculated by eliminating $H_{RT}$ from (3) and represented as

$$H_k = H_{RP}(S_{PP}^{-1} - \Gamma_k^{-1})^{-1}H_{PT}.$$  \hspace{1cm} (4)

The reader can divide and demodulate the signal sets corresponding two antenna groups by beam-forming. For example, when the reader demodulates the signals from Group A, which is composed of tag1,..., $M_P/2$, null beam-forming that directs null directivity to Group B, which is composed of tag$M_P/2 + 1$,..., $M_P$. The beam-forming weight can be calculated from the singular value decomposition (SVD) of the channel between the reader and Group B tags as,

$$[H_{M_P/2+1}, \ldots, H_{M_P},] = [U_B, \tilde{U}_B][S_B, 0]^{1/2}$$  \hspace{1cm} (5)

where $U_B$ and $\tilde{U}_B$ represent signal and noise space eigenvectors, respectively, and $U_B$ is used for receiving signals from Group A since no interference from Group B.
is received by using $\tilde{U}_B$ at the reader. Similarly, the signal sets of Group B can be demodulated in the same manner. Therefore, the proposed method can demodulate the signal of each group discretely.

3 Simulation

3.1 Simulation setup

All the antenna elements in the simulation are half-wave dipoles for simplicity. The frequency is 2.47 GHz, the distance between reader and $P_x$ is 1 m, and the distance between $T_x$ and $R_x$ is 1 m too. The tag element spacing is 0.5 wavelength, and the receiver element spacing is 1.0 wavelength. The transmission power is 20 dBm, and the noise is assumed to be zero-mean Gaussian white. The propagation channel is calculated by Clarke’s model.

3.2 Simulation results

Fig. 3(a) shows BER (Bit-Error-Rate) versus noise power, where the $M_p$ and $M_R$ are 8. From this figure, it is clear that proposed method needs 180-degree hybrid to demodulate the received signals accurately. The deterioration in the curve, ‘w/o hybrid’, is caused by the interference between two antenna groups, and the combination of the beam-forming and 180-degree hybrid successfully suppresses the interference.

![BER versus noise power](image)

### (a) BER versus noise power

![Complexity of MLD versus number of tag antennas](image)

### (b) Complexity of MLD versus number of tag antennas

Fig. 3. Simulation results
this interference. Also, proposed method causes degradation in BER performance compared with the conventional method. Since the proposed method uses null beam-forming, the SNR is slightly degraded.

Fig. 3(b) shows the complexity of MLD versus the number of tag antennas in case of QPSK modulation. The result shows proposed method significantly improves the complexity of MLD. For example, when the number of tag antennas is 8, the search number of conventional method is 65536 per symbol to demodulate all signals from the tags, whereas the search number of proposed method is 256 per symbol. The proposed method becomes more effective when the number of the antennas is increased because the complexity of MLD increases exponentially with the number of tag antennas.

4 Conclusion

This letter has proposed the method to reduce the complexity of MLD in passive MIMO by combining the analog signal processing and digital beam-forming. When the number of the antennas at both reader and tag sides is 8, proposed method can reduce the complexity of MLD to $1/128$ of conventional method, and the effectiveness increases exponentially with the number of antennas. These results show that proposed method is effective in reducing the complexity of MLD in passive MIMO communication.

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Fast and traffic-balanced network recovery from massive failures

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Abstract: When a massive network disruption occurs, repair of the damaged network takes time, and the recovery process involves multiple stages. We propose a fast and traffic-balanced network recovery method that can determine an optimal recovery order of failed physical components reflecting the demand of a balance between maximizing total network flow and providing adequate logical path flows during transient recovery stages. The problem is formulated by mixed integer linear programming. The effectiveness of the proposed method was numerically evaluated, and the results show that with the proposed method, the pareto-optimal recovery order can be determined under the balance between total network flow and adequate logical path flows. In addition, the allocated minimum bandwidth of logical path is drastically improved while maximizing total network flow.

Keywords: network recovery, massive failure, flow control, bandwidth allocation, linear programming

Classification: Network

References

1 Introduction

A massive disruption caused by devastating earthquakes or flooding will damage multiple network components over a wide area. Under this condition, it is difficult to recover sufficient traffic flow by using provisioning of redundant components or protection mechanisms because they are designed for the supposed failure patterns that we have already considered. It is necessary to repair physical resources and reorganize logical paths between network nodes under partial physical resources. Additionally, the amounts of available repair components and manpower are limited, and other infrastructures such as power supply and public transportation will be severely damaged. As a result, after a massive disruption, it takes time to repair a damaged network, and the recovery process will need multiple stages [1]. For effective traffic-flow recovery, we must determine which physical component(s) should be repaired first and how logical paths between network nodes should be reorganized under the available network resources.

Many studies have been done on network recovery. Most of them are focused on repairing single or small-scale failures of physical links and/or logical paths with dedicated or shared redundancy resources such as link/path protection [2].

To determine an effective repair order of failed network components after large-scale failures, the optimal recovery method called progressive network recovery was proposed, where the total amount of traffic for all logical paths during transient recovery stages can be maximized [3]. With this method, traffic can be recovered more effectively compared with the case when it is restored in random order. However, traffic recovery of each logical path is not taken into account. While total amount of traffic can be maximized, the disparity of logical path flows will occur. As a result, the recovery order cannot be optimal from the viewpoint of traffic demands of logical path flows. Therefore, as one of key factors for practical network recovery, it is necessary to consider providing adequate logical path flows.

Some studies on network recovery have investigated bandwidth allocation of logical paths after large-scale failures. In [4], redundant multiple routes for supposed massive failures are pre-designed. When a failure occurs, the most suitable redundant route will be selected among the candidates. Reference [5] proposes a risk modelling methodology that is based on the correlation between physical and logical topology. This method was originally proposed for fault localization but can be applied for designing a network recovery strategy. However, the above methods are based on predesigned redundant physical links and/or logical paths. Especially, the time dimension for network recovery is just a single stage. The optimal recovery order considering multiple recovery stages has not been studied at all.

In this letter, we propose a network recovery method that can determine the pareto-optimal recovery order of failed physical links to meet the demand of a balance between maximizing total network flow and providing adequate logical path flows during transient recovery stages.
2 Assumptions and requirements

We discuss here network recovery problems under the following assumptions.

a) The network model we investigated consists of multi-layer nodes: packet nodes such as IP/MPLS nodes, and transport nodes such as ODU cross-connect or OXC.

b) Logical paths between packet nodes are configured by way of transport nodes, where a logical path is established on one or more physical routes.

c) Physical links in the transport layer are damaged, where each physical link is bidirectional. When a node is damaged, all links contained in the node are considered damaged.

d) Traffic demands between all logical paths are assumed to be equal so as to design a basic bandwidth allocation of logical paths and to evaluate how effective it is.

Two requirements are set to determine the recovery order. One is to maximize total network flow that can be sent between packet nodes during transient recovery stages. The other is to allocate adequate bandwidth for each logical path during transient recovery stages. In this letter, under the assumption d), providing adequate traffic flow for each logical path means minimizing the difference in allocated bandwidth of logical paths.

3 Proposed formulation

We are interested in which physical link(s) should be repaired first during multiple recovery stages in order to meet above requirements. Assume a network $G(N, E)$, where $N$ is the set of nodes and $E$ is the set of links. Set $P$ consists of source-destination pairs, where each pair $p \in P$ consists of a source node $s(p) \in N$ and a destination node $t(p) \in N$.

This problem can be formulated by mixed integer linear programming (MIP), in which the following variables are defined.

- $F_l^p$: Traffic flow of logical path $p$ during recovery stage $l$
- $x_{ijl}^p$: Traffic flow of logical path $p$ on link $(i, j)$ during recovery stage $l$.
- $Y_{ijl}$: Condition of damaged link $(i, j)$ at beginning of recovery stage $l$; $Y_{ijl} = 0$ if damaged link $(i, j)$ is not yet repaired and $Y_{ijl} = 1$ when link $(i, j)$ is repaired.

Equation (1) is the proposed objective function formula considering adequate bandwidth allocations of logical paths. Two terms are combined in order to meet the demand of a balance between total network flow and adequate logical path flows. The first term maximizes the traffic recovery ratio during transient repair stages, and is based on [3]. The upper band of total network flow, which is the sum of the available bandwidths of logical paths after all links have been repaired, is denoted as $M$. Parameter $ph$ is the number of multiple repair stages.

The second term indicates the difference in allocated bandwidths of logical paths. Various formulas such as [6] can be used to compute the difference in allocated bandwidth. In this letter, to understand the basic characteristics of bandwidth allocations of logical paths, we use a simple formula that compares the allocated bandwidth between logical paths with adjacent path numbers, $F_l^p$ and $F_{l-1}^p$. Notice that it is easy to extend the term for different traffic demands between logical paths.
The two terms in Eq. (1) have a trade-off relation in general. The intensity between the two terms depends on the network operation policy, traffic demands and so on. To meet the required balance, by changing $\lambda$, the pareto-optimal recovery order of damaged physical links can be solved.

$$\text{minimize } \lambda \left( M - \sum_{l=0}^{ph} \sum_{p \in P} F_l^p \right) + (1 - \lambda) \sum_{l=0}^{ph} \sum_{p \in P} |F_l^p - F_l^{p-1}|$$

subject to

$$\sum_{j \in (i,j) \in E} x^p_{ijl} - \sum_{j \in (j,i) \in E} x^p_{jil} = \begin{cases} F_l^p & \text{if } i = s(p) \\ -F_l^p & \text{if } i = t(p), p \in P, i \in N, l = 0, \ldots, ph \\ 0 & \text{otherwise} \end{cases}$$

(2)

$$\sum_{p \in P} x^p_{ijl} \leq C_{ij} \left( y_{0ij} + \sum_{k=1}^{l} Y_{ijk} \right), \quad (i,j) \in E, \quad l = 0, \ldots, ph$$

(3)

$$\sum_{(i,j) \in E} Y_{ijl} \leq 2, \quad l = 1, \ldots, ph$$

(4)

$$Y_{ijl} = Y_{jil}, \quad (i,j) \in E, l = 1, \ldots, ph$$

(5)

$$y_{0ij} + \sum_{h \neq g} Y_{ijh} = 1, \quad (i,j) \in E$$

(6)

Equations (2) to (6), are recovery constraints introduced here. Constraint (2) is due to the flow conservation requirement, and constraint (3) to capacity limitation. The value of $y_{0ij}$, the binary value, indicates the condition of physical link $(i,j)$ just after a massive disruption occurs. Link $(i,j)$ with $y_{0ij} = 1$ is not damaged, and those with $y_{0ij} = 0$ are damaged. The term $C_{ij}$ is the capacity of physical link $(i,j)$. Constraints (4) and (5) mean that all links are bidirectional, and when a link is repaired, both directions are simultaneously repaired. Constraint (6) means that each link can be recovered once through all recovery stages, where parameter $g_{ij}$ is introduced to express the stage after which link $(i,j)$ will be available.

In general, the problem of the MIP method is NP-hard. We have confirmed that the computation time of the MIP increases in an exponential fashion as the number of repaired links increases. To apply to larger-scale failures, an approximate algorithm will be necessary when it is difficult to solve problems in practical time with the MIP method.

4 Performance evaluations

We evaluated the effectiveness of the proposed method from two perspectives, the optimal recovery order and the improvement of logical path flows, by using the GLPK (GNU Linear Programming Kit) solver, where every damaged link can be available from the first stage, $g_{ij} = 1$ in (6).

Fig. 1 shows the results of the optimal recovery order that can meet the demand of a balance between maximizing total network flow and providing adequate logical path flows. Fig. 1(a) is a network model evaluated here. Fig. 1(b) shows the recovery order and traffic flows at each recovery stage. In this letter, since traffic demands between all logical paths are assumed to be equal, we pay attention to the...
minimum path flow. The results indicate that the proposed method can determine an optimal and practical recovery order reflecting the demand, where in case of $\lambda = 0.5$, the recovery order providing equal bandwidth for all logical paths is determined. On the contrary, in case of $\lambda > 0.7$, the recovery order that can maximize total network flow is determined, where the result is almost equal to that of the conventional method that aims to maximize total network flow.

Fig. 1(c) shows results of trade-off relations between total network flow and minimum path flow through all recovery stages. The horizontal axis shows the difference rate of the minimum path flow, where the minimum path flow accumulated through all recovery stages is compared with the ideal path flow that is computed by dividing total network flow by the number of logical paths. When the difference rate is smaller, logical path flows are allocated more adequately. The vertical axis shows the total network flow rate, which is computed by comparing total network flow of the proposed method with that of the conventional one. The results indicate that the pareto-optimal recovery corresponding to the demand of a balance between the two terms can be designed by selecting the appropriate value of $\lambda$.

Table I shows the improvement of the minimum path flow under the condition of maximizing total network flow. The values show the difference rate of the minimum path flow that is defined above. We prepared for five sample network models. Five random failure patterns in each network model with five damaged links are evaluated to obtain each value, and the average rates are shown. Compared with the conventional method, the characteristics of the minimum path flow are drastically improved in all network models.
5 Conclusion

We proposed a new network recovery method that can determine an optimal recovery order of damaged physical links under the demand of a balance between maximizing total network flow and providing adequate logical path flows. We evaluated basic numerical performance and confirmed that the pareto-optimal recovery order corresponding to the demand can be designed. In addition, the characteristics of logical path flows are drastically improved under the condition of maximizing total network flow, compared with a conventional method that aims to maximize total network flow.

Table I. Sample network models and the defined difference rate of the minimum path flow through all recovery stages under the condition of maximizing total network flow. The rate is smaller, path flows are allocated more adequately.

<table>
<thead>
<tr>
<th>Network</th>
<th>No. of transport nodes</th>
<th>No. of physical links</th>
<th>No. of logical paths</th>
<th>Proposed</th>
<th>Conventional</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11</td>
<td>14</td>
<td>16</td>
<td>0.556</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>11</td>
<td>25</td>
<td>20</td>
<td>0.069</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>31</td>
<td>20</td>
<td>0.152</td>
<td>1</td>
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<tr>
<td>5</td>
<td>50</td>
<td>200</td>
<td>20</td>
<td>0.334</td>
<td>1</td>
</tr>
</tbody>
</table>

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Massive MIMO effect for multiuser spatial multiplexing in time varying channel

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Abstract: The higher beamforming gain of massive MIMO is expected to improve the link budget shortfall in higher frequency bands. We note that, in multiuser MIMO, the beamforming gain for desired terminal is also effective in overcoming inter-user interference (IUI) caused by channel time variation. Computer simulations show that the SIR performance can be improved over 20 dB by increasing the number of base station antenna elements from 2 to 100.

Keywords: massive MIMO, multiuser MIMO, channel time variation, inter-user interference

Classification: Wireless Communication Technologies

References

1 Introduction

Handling data traffic which is rapidly exploding is a serious issue for mobile service operators [1]. Since the frequency resources are limited, the usage of higher frequency bands (i.e. millimeter-wave) is being considered to obtain higher capacity in future radio access system such as 5th generation (5G) mobile communications [2]. The key challenge for usage of higher frequency band is link budget shortfall. The propagation loss becomes large and the performance of radio frequency (RF) components such as high power amplifier (HPA) is limited in higher frequency band. Application of massive MIMO [3] is one of the promising solutions to compensate it. Massive MIMO can realize large beamforming gain with huge numbers of arrayed antenna elements without high-performance high-cost RF components [4].

Another approach to obtain higher capacity is known as multiuser MIMO, in which mobile terminals (MTs) are spatially multiplexed with the same frequency channel at the same time [5]. Channel environments in higher frequency bands are considered to be dominated by Line-of-Sight (LoS) component since base station (BS) or MTs are required to equip highly directive antennas in order to obtain transmission/reception gain. In such situation, multiuser diversity gain is expected to increase the system capacity because the inter-user correlation between the MTs is lower than intra-user correlation. To spatially multiplex several MTs, the BS requires channel state information at the transmitter (CSIT) to suppress inter-user interference (IUI). The accuracy of CSIT is deteriorated by the channel time variation caused by the movement of the MTs or some objects around the MTs. Inaccurate CSIT causes incomplete IUI suppression which degrades the Signal-to-Interference power Ratio (SIR) performance of multiuser MIMO [6].

![Beam pattern of antenna array.](image)

(a) Conventional multiuser MIMO

(b) Multiuser massive MIMO

Fig. 1. Beam pattern of antenna array.
In massive MIMO, the higher beamforming gain of the transmission signal is obtained. For example, Fig. 1 shows the beam patterns of (a) conventional multi-user MIMO and (b) multiuser massive MIMO. In conventional multiuser MIMO, where the number of BS antenna is almost the same as that of the total MTs antennas, the IUI suppression via null-steering is only performed (dashed arrows). In contrast, the beamforming is additionally performed to the desired MTs (bold arrows) in multiuser massive MIMO. It is expected to improve the SIR performance. This paper examines this beamforming effect by large arrayed antennas in multiuser MIMO time varying channels.

2 System assumptions and computer simulations

Simulation parameters are shown in Table I. We consider the small cell environment of high frequency band systems, the frequency and the cell radius are set to 20 GHz and 20 m, respectively. The number of BS antenna elements, $N_t$, is increased from 2 to 100. A uniform linear array is employed to regularize antenna correlation effect as number of antenna elements. For the sake of simplicity, each MT is assumed to have only one antenna element. $N_r$ MTs are uniformly distributed within the 120° sector cell and the height difference between BS and MTs is assumed to be 10 m. MTs move linearly in random directions at constant speed. We assume a Nakagami-Rice fading channel with Rician factor $K = 10$ dB. The channel matrix $H \in \mathbb{C}^{N_r \times N_t}$ is expressed as follows:

$$
H = \sqrt{\frac{K}{K+1}} H_{\text{LoS}} + \sqrt{\frac{1}{K+1}} H_{\text{NLoS}},
$$

where $H_{\text{LoS}}$ is determined by the spatial relationship of the BS and MTs:

$$
H_{\text{LoS}} = \begin{bmatrix}
e^{-j2\pi d_{11}} & \ldots & e^{-j2\pi d_{1N_t}} \\
\vdots & \ddots & \vdots \\
e^{-j2\pi d_{N_r1}} & \ldots & e^{-j2\pi d_{N_rN_t}}
\end{bmatrix},
$$

Table I. Simulation parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>20 GHz</td>
</tr>
<tr>
<td>Cell</td>
<td>Sector = 120° radius = 20 m</td>
</tr>
<tr>
<td>BS Antenna Array, $N_t$</td>
<td>Linear 2–100 elements 0.5(\lambda) spacing</td>
</tr>
<tr>
<td>BS Antenna Elements</td>
<td>Directional [7]</td>
</tr>
<tr>
<td>Number of MT, $N_r$</td>
<td>2 (Omnidirectional 1 element/1 MT)</td>
</tr>
<tr>
<td>MT Speed</td>
<td>4, 10, 40 km/h</td>
</tr>
<tr>
<td>(f_D)T_S = 4.9 \times 10^{-4}, 1.2 \times 10^{-3}, 4.9 \times 10^{-3})</td>
<td></td>
</tr>
<tr>
<td>Channel Model</td>
<td>Rician $K = 10$ dB</td>
</tr>
<tr>
<td>Channel Estimation</td>
<td>Ideal (200 symbols (= 1.3 ms) period)</td>
</tr>
<tr>
<td>Symbol Length</td>
<td>6.67(\mu)s</td>
</tr>
<tr>
<td>MIMO Weight</td>
<td>Gram-Schmidt orthogonalization</td>
</tr>
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</table>
where $d_{ij}$ is the distance between the $j$-th BS antenna element and the $i$-th MT antenna element and $\lambda$ is the carrier wavelength. The channel time variation of $H_{\text{LoS}}$ is calculated by the spatial relationships between the BS and the MTs. $H_{\text{NLoS}}$ is the multipath component from the scatters which are uniformly sited around the MTs. The spatial correlation between the BS antenna elements are considered by using Kronecker model [8].

$$H_{\text{NLoS},i} = R_{t,i}^{1/2} H_{\text{iid},i}^{1/2} H_{\text{NLoS},i}^{1/2},$$  \hspace{1cm} (3)

$$H_{\text{NLoS}} = \left[ H_{\text{NLoS},1}^T, \cdots, H_{\text{NLoS},Nt}^T \right]^T,$$  \hspace{1cm} (4)

where $H_{\text{NLoS},i} \in \mathbb{C}^{1 \times Nt}$ denotes multipath components for the $i$-th MT and $R_{t,i} \in \mathbb{C}^{Nt \times Nt}$ is calculated by the approximate formula in [9]. $R_{t,i}$ becomes 1 since each MT has 1 antenna. They are multiplied to an independent identically distributed (i.i.d.) Rayleigh fading channel matrix, $H_{\text{iid},i} \in \mathbb{C}^{1 \times Nt}$. The channel time variation of $H_{\text{iid},i}$ is generated by Jakes’ model [10] with 8 scatters. The Power Azimuth Spectrum (PAS) is set to 10°. The channel estimation and weight calculation are assumed to be performed ideally, immediately and periodically. Here, we focus only the effect of the channel time variation. The estimation period is set to 200 symbols (i.e. 1.3 msec). Performance is evaluated by SIR. The SIR is calculated for all symbols between the estimation periods.

Fig. 2(a) shows cumulative distribution function (CDF) 50% value of the SIR versus the number of BS antennas, at the MT speeds of 4, 10, and 40 km/h. Increasing the BS antenna element number improves the SIR performance at each MT speed. For example, increasing 2 to 100 elements improves the SIR by over 20 dB at the MT speed of 4 km/h.

Fig. 2(b) shows CDF 50% values of the relative signal (S) and the interference (I) power versus the number of BS antennas. Power is normalized by the reception power in the SISO case. Beamforming offered by the many BS antenna elements improves the signal power whereas it doesn’t affect to the IUl power. Signal power from large arrayed antenna is coherently combined at desired MT while interference signal propagates to the other MTs at random phase. This is reason why SIR is improved. The improvement of the signal power is about 20 dB which is larger than the theoretical beamforming gain from 2 to 100 elements; $10 \log_{10}(100/2) = 17$ dB. The orthogonalization in the spatially correlated channel deteriorates the signal power with the few BS antenna elements. As shown in Fig. 2(b), the signal power exhibits lower than 0 dB when the elements are fewer than 8. Interference power is also slightly increased in the fewer antenna elements region, it is also due to the correlated channel. Such disadvantages can be effectively compensated by enlarging arrayed antenna.

Fig. 2(c) plots the relationship of CDF 50% value of relative signal and IUl power versus symbols index (i.e. time) from the instance of channel estimation at the MT speed of 40 km/h. The signal power obtained by 100 elements is almost constant at 10 dB while that of 2 elements is constant at $-8$ dB. The IUl power cannot be suppressed at the instance that channel estimation is performed, but it rapidly increases with time and converges to about $-10$ dB. This indicates that slight phase transition by channel time variation immediately breaks steered null whereas signal
beamforming is robust to that. Additionally, its beamforming gain is much higher than IUI power. From the above observations, stable communication with the SIR value of 20 dB is realized by applying massive MIMO without any additional techniques such as channel prediction.

Fig. 2. Simulation results.
3 Conclusion

This paper examined the performance of multiuser massive MIMO in time varying channels. We clarified the relationship between the number of BS antenna elements and the SIR performances of conventional and massive MIMO via computer simulations. SIR improvement of over 10 dB is achieved by increasing the number of BS antenna elements from 2 to 100. It was shown that massive MIMO can achieve stable communication even under high mobility condition without any additional techniques.