THE NUMERICALLY STABLE QRD-DMS RECEIVER AND OVERLAPPED CHANNEL TRANSMISSION TECHNIQUE FOR SLOW FREQUENCY HOPPED MULTIPLE ACCESS NETWORKS

Shang-Chieh Liu and Evaggelos Geraniotis

Electrical Engineering Department and Institute for System Research
University of Maryland, College Park, Maryland 20742
email: nian@eng.umd.edu, evagelos@eng.umd.edu

ABSTRACT

In this paper, we present an overlapped channel transmission (OCT) multiple access scheme which increases the uplink capacity of the slow FHMA systems. By using antenna arrays techniques, subscribers can transmit data through time-frequency overlapped slots and the proposed system increases the spectrum efficiency. A practical system that uses 2-fold OCT to increase system capacities with the same total bandwidth will be proposed along with a fast processing and numerically stable beamforming algorithm and VLSI architecture. The beamforming weights can be calculated in one symbol's duration and thus coherent combining can be achieved to further increase the beamforming performance.

1. MOTIVATIONS

The commonly used access techniques for slow frequency hopped multiple access (FHMA) or time division multiple access (TDMA) systems do not allow users to simultaneously share the same frequency spectrum like direct sequence code division multiple access (DS/CDMA) does. While the next generation wireless networks require not only higher spectral efficiency but also higher data rate, DS/CDMA schemes may need expensive equalizers to mitigate the severe multipath propagation which is caused by the high chip rate transmission. To avoid such difficulties motivates the research in technique that increase the spectrum usage as well as the system capacity in FH/TDMA networks. In this paper, we introduce an Overlapped Channel Transmission (OCT) method together with a high speed beamformer, which allows several users to share the same frequency-time slot so as to increase the spectrum usage.

Fig. 1 shows our proposed 2-fold OCT system which can accommodate almost double the useful number of channels in the same bandwidth. In the proposed system, if two overlapped users are very close to each other in location, the problem is similar to the frequency collisions in FHMA systems [1], and we call it 'partial collisions' since both users partially share the same frequency. Interleaving and Reed-Solomon hopping patterns can be used to combat partial collisions in military applications. For commercial systems, we can assign or reassign channels according to intended user's channel vector in order to avoid partial collisions, but this is beyond the purpose of this paper.

Previous array processing systems have been suggested that allow several users to share the same frequency at the same time, like the Space-Diversity Multiple Access (SDMA) systems [2]. Excluding the usage of sectorized antenna, the beamforming algorithms for the SDMA systems depend on either training sequence, i.e. LMS or RLS algorithm, or some other blindly adaptive beamforming algorithm, i.e. MUSIC or CMA. But training sequences waste useful bandwidth as well as a certain percentage of each dwell. The MUSIC [3] method, beside the high complexity of eigenvalue decomposition methods, line of sight propagations may not always be available in terrestrial transmission. The drawbacks of Constant Modulus Algorithm (CMA) are slow convergence and high receiving signal to interference and noise ratio (SINR) required for satisfactory performance, which is not interested in FHMA systems since FHMA needs fast convergence beamforming algorithm and low SINR jamming-rejecting capability.

Another approach is to maximize the receiving signal to interference and noise ratio (SINR). Bakhru [4] first proposed the Maxmin beamforming algorithm that maximizes the received SINR with gradient descent search. Liu [5] applied power iterations to the dominant eigen-mode searching (DMS) problem, which reduced the computational complexity of the beamformer. Since power iterations always converge faster than correlation matrices' estimators, the DMS method converges much faster and performs better than the Maxmin algorithm.

To further improve the beamforming performance and reduce the effects of truncation errors due to finite-digit sampling, a QR-decomposition DMS (QRD-DMS) algorithm is proposed in this paper which is more numerically stable than the original DMS method. The only known method that solves generalized eigenvalue decompositions from data domain is to use generalized singular value decomposition (GSVD). However, to use GSVD we must apply cosine-sine (CS) decomposition [6] which is very computational intensive. The proposed QRD-DMS method implements a simple data transform to skip complicated and expensive CS-decompositions. A systolic structure is also proposed for VLSI design. Since there is no decision feedback loop in our beamformer, it is free from error propagations. Coherent weight combining can be easily achieved to further improve the beamforming performance. The performance and convergence behaviors of our blind QRD-DMS algorithm is compared to that of QRD-RLS [7] algorithm, the best known unblind beamforming algorithm.

2. SYSTEM MODEL

We assume the signals are modulated by balance-DQPSK, and sent out to the N-fold OCT multipath fading channels.
The multipath propagation model is assumed to be L-paths multi-scattering [2] with $\Delta \theta$ arriving angle spread. There is a phase array with $p$ elements at the base station. The data reception of each user is implemented by three low pass filters: BPF, LRF and RRF. As depicted in Fig. 2, the band pass filter (BPF) selects the desired data $s_i(t)$. The left reject filter (LRF) and right reject filter (RRF) detect the very low frequency responses of the overlapped users as interference. Before we go to details, we have to define two types of interference. Overlapping interference comes from the users whose channels partially overlap with the desired one. Adjacent interference comes from the imperfect slope of low pass filters of the adjacent isolated channels, which is one full bandwidth away. Both interference ($I_{k,l}(t)$) plus the background (thermal) noise ($n_0(t)$) interfere the desired signal because of overlapping transmission. Therefore, the received data ($r_2(t)$) at the BPF can be expressed as

$$ r_2(t) = \sum_{k=1}^{2N} \sum_{l=1}^{L} I_{k,l}(t) + n_0(t) \tag{1} $$

where

$$ s_i(t) = \sqrt{P_i} b(t - \tau_i) e^{-j\phi_i} a_i $$
$$ I_{k,l}(t) = \sqrt{P_{k,l}} i_{k,l}(t) e^{-j\phi_{k,l}} a_{k,l} \tag{2} $$

$P_{k,l}$ means the receiving power of the $k^{th}$ user and $l^{th}$ path; $b(t)$ means the transmitted data; and $i_{k,l}(t)$ is the interference partially included by the BPF. The $\tau_i$ is the arrival delay of the $l^{th}$ path, and $\phi_{k,l}$ is the phase error caused by the arrival delay and fading. The total number of interference equal to $2N$, which includes $2N - 2$ overlapping interference and two adjacent interference. Channel vectors $a_{k,l}$ is a $p \times 1$ complex vector, which is a function of the arrival angle and geometry of the sensor array. For a linear uniform array, we can model the channel response from, which set groups from different path delays. If we further consider the rays of similar arriving angles as a sub-group in each path group, the channel response yields to

$$ a_{\alpha,l}(\psi_i) = \sum_{m=1}^{M} \tilde{g}_{m,l} e^{j\alpha(\psi_i + \Delta_m)} \quad \alpha = 0, \ldots, p - 1. \tag{3} $$

where $a_{\alpha,l} = [a_{0,l}, a_{1,l}, \ldots, a_{p-1,l}]^T$, and $M$ is the number of distinguishable rays in arriving angle of $l^{th}$ path. The coefficients $\tilde{g}_{m,l}$ are zero-mean complex Gaussian random variables. The phase perturbation $\Delta_m$ is also zero-mean from the assumption of angle diversity and scattering multipath. The digital data can be sampled after an integrator

$$ x_i(n) = \int_{\tau_i+(n-1)\tau_b}^{\tau_i+n\tau_b} r_2(t)dt $$
$$ = s_i(n) + u_i(n) \tag{4} $$

where $\tau_b$ is a symbol’s duration, and $u_i(n)$ is the total interference plus noise. LRF and RRF has the same bandwidth as the guardband. The received data in both rejecting filters is added up to estimate the rejecting signal $r_z(t)$ as shown in Fig.3.

$$ r_z(t) = \sum_{k=1}^{2N} \sum_{l=1}^{L} I_{k,l}(t) + \tilde{n}_0(t) \tag{5} $$

where

$$ \tilde{n}_0(t) = \sqrt{\tilde{P}_0} \tilde{i}_0(t) e^{-j\phi_{0,l}} a_{0,l} \tag{6} $$

We assume that channels response are the same over a channel bandwidth. The channel vectors in equation (2) and (6) are just a (complex) constant away, and we include such a complex constant in $i_{k,l}(t)$. The digital data of the rejecting bands are

$$ x_i(n) = \int_{\tau_i+(n-1)\tau_b}^{\tau_i+n\tau_b} r_z(t)dt \tag{7} $$

3. OCT METHOD

3.1. DMS beamformer

Beamforming weights to maximize the average signal to interference and noise ratio (SINR) equals to the following problem

$$ \max_{w \neq 0} \frac{E[|w^{H} s_i|^2]}{E[|w^{H} u_i|^2]} \Rightarrow \max_{w \neq 0} \frac{w^{H} R_{zz,l} w}{w^{H} R_{uu,l} w} \tag{8} $$

Figure 2: Frequency allocation of BPF, RRF, and LRF.

Figure 3: The architecture of OCT base station.
We have assumed that signal sources are mutually uncorrelated. If we further assume that the background noise is white, we can have the following equation for 2-fold OCT systems

$$R_{uu,I} = \frac{B-1}{2} R_{zz,I} + \frac{1}{B} \sigma_0^2 I,$$  \hspace{1cm} (9)

where $\eta$ means the average spectrum magnitude ratio of higher frequency to DC part. Since the perturbation term from white noise is so small we can approximate the above equation to $R_{uu,I} = \kappa R_{zz,I}$, where $\kappa$ is a constant. Without changing the validity, we can replace the term $R_{uu,I}$ in the above equation by $R_{zz,I}$, which can be estimated from the output of rejecting filters.

Since both correlation matrices $R_{xx,I}$ and $R_{zz,I}$ are positive definite, for any 2-norm unit vector $w \neq 0$, we have [6]

$$\lambda_1 \geq \frac{w^H R_{xx,I} w}{w^H R_{zz,I} w} \geq \lambda_p$$  \hspace{1cm} (10)

where $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p > 0$ are the ordered general eigenvalues of matrix pair $(R_{xx,I}, R_{zz,I})$. The maximum average SINR happens when the weight vector equal to the principle eigenvector of the matrix pair, that is,

$$R_{xx,I} \cdot w_{opt} = \lambda_{max} \cdot R_{zz,I} \cdot w_{opt}.$$  \hspace{1cm} (11)

### 3.2. QRD-DMS Beamformer

In this subsection, we propose a novel method to solve the generalized eigenvalue decomposition from the data domain, which is more numerically stable. The most popular method to estimate the correlation matrices is to average vector’s outer products in an exponentially decreasing window.

$$R_{xx}(n) = \mu R_{xx}(n-1) + x(n)x^H(n),$$

$$R_{zz}(n) = \mu R_{zz}(n-1) + z(n)z^H(n).$$  \hspace{1cm} (12)

We can rewrite the above correlation estimations by the product of exponentially decay data matrices.

$$R_{xx}(n) = X(n)^H \cdot X(n),$$

$$R_{zz}(n) = Z(n)^H \cdot Z(n),$$  \hspace{1cm} (13)

where $X(n)$ and $Z(n)$ are $n \times P$ data matrices, and

$$X(n) = \left[ \mu^{(n-1)/2} x(1), \mu^{(n-2)/2} x(2), \ldots, x(n) \right]^T,$$

$$Z(n) = \left[ \mu^{(n-1)/2} z(1), \mu^{(n-2)/2} z(2), \ldots, z(n) \right]^T.$$  \hspace{1cm} (14)

The original generalized eigenvalue decomposition problem (11) becomes

$$\{X^H(n)X(n)\} \cdot w_{opt}(n) = \lambda_{max} \cdot \{Z^H(n)Z(n)\} \cdot w_{opt}(n).$$  \hspace{1cm} (15)

However, correlation matrices’ estimation by data vectors’ outer products enlarges the truncation errors caused by the finite-digit sampling. To avoid this error enlargement, we prefer to update our beamformers directly from the data domain rather than from the correlation domain. The only known method to solve the above eigen-decomposition problem in data domain is to solve the generalized singular value decomposition (GSVD) [8] of matrix pair $(X(n), Z(n))$. However, the GSVD is very computational intensive when doing the CS decompositions. Furthermore, we only interest in dominant eigen-mode rather than all the other eigenvalues and eigenvectors. Using GSVD to find all the eigen modes is hardware too expensive in our beamforming problem. Therefore, we prefer another method to solve it from the data domain via QR-decomposition [9]. The beamforming systolic architecture is also proposed to find the principle eigenvector (optimal weight vector). We summarize the QRD-DMS algorithm as follows

1. Transfer matrices $X$ and $Z$ into matrix $A$ and $B$.

$$A = (X + Z),$$

$$B = (X - Z).$$  \hspace{1cm} (16)


$$\begin{bmatrix} A \\ B \end{bmatrix} = Q \begin{bmatrix} R \\ O \end{bmatrix}.$$  \hspace{1cm} (17)

3. Do the same rotation to matrix $[B^H A^H]^H$ to get the $P \times P$ matrix $H$.

$$\begin{bmatrix} H \\ F \end{bmatrix} = Q^H \begin{bmatrix} B \\ A \end{bmatrix}.$$  \hspace{1cm} (18)

4. Find the principle eigenvector of matrix pair $(H, R)$ as the QRD-DMS beamformer.

$$H \cdot w_{opt} = \lambda_{max} \cdot R \cdot w_{opt}.$$  \hspace{1cm} (19)

We give a simple proof of the QRD-DMS algorithm. The details are given in [9].

**Proof**: From above equations, we have $X = (A + B)/2$ and $Z = (A - B)/2$. The generalized eigenvalue problem in equation (15) can be written as

$$(A + B)H(A + B) \cdot W = (A - B)H(A - B) \cdot W \cdot A \Rightarrow (A^H B + B^H A) \cdot W = (A^H A + B^H B) \cdot W \cdot A \Rightarrow [A^H B^H] \begin{bmatrix} B \\ A \end{bmatrix} \cdot W = [A^H A + B^H B] \begin{bmatrix} A \\ B \end{bmatrix} \cdot W \cdot A \cdot \lambda.'$$  \hspace{1cm} (20)

From the definitions of the matrices $R$ and $H$,
\[
\begin{bmatrix}
R(n) & H(n) & R^{-H}(n) \\
o & # & # \\
o_{2xP} & # & # 
\end{bmatrix} = T(n)
\begin{bmatrix}
\mu^{1/2}R(n-1) & \mu^{1/2}H(n-1) & \mu^{-1/2}R^{-H}(n-1) \\
o & # & # \\
\alpha^H(n) & \beta^H(n) & 0 \\
\beta(n) & \alpha^H(n) & 0
\end{bmatrix}
\]

Since the upper triangular matrix R is non-singular as the intersection of X and Z is non-null, we can take it out at the both sides of the above equation.

\[
H \cdot W = R \cdot W \cdot \Lambda'
\]

where \( \Lambda' = (A-I)/(A+I) \) is a diagonal matrix. Since \((Y^HY) \) and \((Z^HZ) \) are all positive, A is positive and so is the \( (A+I) \). This means that \( \Lambda' \) always exists and is finite. \( \square \)

We can use power iterations [8] to find the above principle eigenvector cheaply. By the fact that power method always converges faster than the estimation of correlation matrices, we can just use power method once in every beamforming weight updating. The other useful index is the intended user’s channel vector. Especially when we want to avoid partial collisions, we can assign the similar users (in channel vectors) far from each other in the frequency domain. The optimal beamformer and the corresponding channel vector can be estimated by

\[
\hat{w}_{opt}(n) = R^{-1}(n) \cdot (H(n) \cdot \hat{w}_{opt}(n-1)), \\
\hat{a}_0(n) = \kappa_0 \cdot R(n) \cdot (H(n) \cdot \hat{w}_{opt}(n-1)),
\]

where \( \kappa_0 \) is a constant.

After we show that how to easily solve the generalized eigenvalue problem in data domain, we’ll like to see the corresponding VLSI designs for OCT beamformers. From the definitions of the A and B data matrices, we let

\[
\alpha(n) = x(n) + z(n), \\
\beta(n) = x(n) - z(n)
\]

To find the desire matrices R(n), H(n) and R^{-1}(n), the \( P \times 1 \) vectors \( \alpha(n) \) and \( \beta(n) \) are feed into a systolic architecture, and the QR-decomposition is achieved by series of Given rotations [7], T(n). The final matrix updating formula can be expressed as top.

Fig. 4 shows the resulting systolic array to find the optimal beamformer. It combines the given rotations and the power iterations together. To reduce the processing delay and let the power method update the beamformer from the lastest weight vector, we can pipeline more than P users into systolic array in a symbol’s duration. This increases the operating frequency to 2P times the symbol rate, but it is easily achievable by the present VLSI technology. For example, the computation in each cell can be done within 30ns, which involves 6 multiplications, by the present 0.3um BiCMOS technology. If we pipeline 16 users into our systolic processor, we can parallelly calculate the beamforming weights of these 16 users in one symbol’s duration, where the transmission rate of each user is 1M symbol per second. The resulting beamformer’s processing time is so short that, we can use coherent weight’s combining to further enhance the beamforming performance.

4. SIMULATION RESULTS

In our simulations, we consider the mobiles-to-base station communications of a single cell system. The channel and rejecting (guard) bandwidth are 28KHz and 2KHz respectively and the carrier frequency is 2.5GHz. We take a linear low pass filter with a slope 18dB/oct as the BPF, RRF and LRF.

There is a n-element uniform linear array antenna at base station. Each antenna element is separated by a equal distance of a half carrier wavelength. Since the channel bandwidth is far less than the multipath frequency, we use the flat fading multi path model where ray’s group \( M = 10 \), as we have shown in equation (3). The received power per bit of a specific user \( E_b/N_0 = 6dB \) above the white noise level. Since both pass band and rejecting band contain the signals of same (overlapped) users, we assume that the correlation of received signal of the same users in pass band (\( i_1 \)) and rejecting band (\( i_2 \)) is 0.2. Modulation error and fading phase is randomly over [0, 2\( \pi \)]. The intended user arrives from \( \pi/5 \) (36°) while any other users randomly distribute over [0, 2\( \pi \)] in azimuth around the base station. There are two strong jammers arrive from 72° and –180° with the Jammer-to-Signal ratio (J/S) 40dB and 30dB respectively. We assume the arriving angle spread \( \Delta \theta = 60° \), and is uniformly distributed. To check the convergence of QRD-DMS beamformer, channels are assumed unchanged within the dwell time, say 200 symbols.

Since 2-fold OCT double the number of physical channels in the same bandwidth, for a fair comparison, we need to examine the performances of both systems operating at the same throughput rate. For instance, we can compare our overlapping system using D-QPSK to a nonoverlapping system using 16-QPSK. Fig. 5 compares the different cases of uncoded BER : 2-fold OCT + D-QPSK (X2), nonoverlapped
Center frequency \( (f_c) \) 2.5 GHz
Total hopping range 70 MHz
Bandwidth of channels 30 KHz
Hopping interval 200 bits
Arriving Angle 36°
Angle diversity 60°
Exp. window factor \((\mu)\) 0.99
Signal-to-noise \((E_b/N_0)\) ratio 6 dB
Jammer-to-signal power \((J/S 1)\) 40 dB at 72°
Jammer-to-signal power \((J/S 2)\) 30 dB at –108°

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<th>Table 1: Parameters of FHMA networks</th>
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D-QPSK (X1), nonoverlapped D-8PSK (X1.5), and nonoverlapped D-16PSK (X2). We find that the overlapping system performs better before partial collisions dominate the performance. Moreover, the beamforming resolution increases as the number of antenna element increased. Fig. 6 shows the uncoded bit error rate versus \(E_b/N_0\) when number of antenna element equals 11. Compare to the previous result, we find that the performance of 2-OCT+DQPSK increases faster than which of Non-OCT+D16PSK while both systems achieve the same throughput rate.

After comparing the proposed OCT system to the nonoverlapped ones, we would like to compare our blindly adaptive QRD-DMS beamforming algorithm to the QRD-RLS algorithm which assuming training sequences are used during the experimental time. Fig. 7 shows the uncoded bit error rate versus the iterations. One iteration means one symbol's duration as well as one updating in the beamforming weights. As we can see that, our proposed QRD-DMS algorithm converges as fast as the QRD-RLS one, and both algorithms have similar performance. However, the latter system sends no information at all but only training sequences.

5. CONCLUSION
In this paper, we propose a new overlapped channel transmission method which allows one channel overlaps with the others by using beamforming techniques. The numerically stable beamforming algorithm (QRD-DMS) is also introduced for high speed (parallel) blind processing the weight computations. With the present industry technology (0.3µm), the proposed systolic processor can support 16M symbols per second, i.e. handle 16 users with 1M symbol rate at a time. The proposed system not only increases the frequency spectrum efficiency, eliminates the strong intended jammers but also blindly updates the beamformer and converges very fast.

6. REFERENCES