Joint beam adaptation in 60GHz interference channel via sequential stochastic approximation

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***Abstract*—The best beam directions for Q coexisted 60GHz radio systems are jointly determined to maximize the sum rate. Capturing the directional characteristic of 60GHz indoor interference channel, a joint discrete optimization problem is properly established with the objective function evaluated from the noisy channel estimates. In addition to the conventional exhaustive search (ES) method, we propose a simulation based sequential stochastic approximation (SSA) algorithm with segmented indicator to solve the problem in an adaptive way. Although only the sub-optimal solution can be guaranteed in practice, the proposed algorithms are demonstrated to be more efficient and practical to implement than beam search in brute force, especially in dense network. Also, they exhibit good flexibility and feasibility for different usages in tradeoff between performance and complexity.**

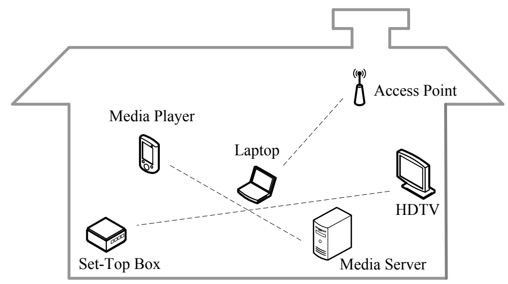

Fig. 1. A typical 60GHz indoor communication scenario with multiple coexisted systems

I. Introduction

Nowadays, 60GHz wireless communication is regarded as the most promising technology in short range high-speed indoor wireless communication [1]. An ultra high data rate beyond several Gbps can be afforded by the huge available bandwidth (>7GHz) and the use of compact size multi-antenna arrays. Since a directional antenna pattern is usually formed (by phased array) or steered (by directive steerable antennas) to compensate the high propagation loss in this band, tuning the beams in right directions has become an important task to guaranteed the rigid quality of service requirement, especially when multiple coexisted systems are evolved. Due to the interference impact, determining the optimal directions for the transmitter (Tx) and the receiver (Rx) in each system seems more intricate than just pointing the transceivers toward each other directly.

The coexistence problem in wireless interference channel was mainly concerned in the sense of the omni-directional propagation [2] but seldom mentioned on the directive transmission. Recently, the beam switching (BS) has been adopted in IEEE 802.15.3c WPAN [1] standard for 60GHz communication, in which the best directive beam is found and switched within a predefined codebook without complex pattern estimation [3]. However, as more and more parallel systems with finer beams are involved, joint beamforming in brute force (such as the conventional exhaustive search, ES) or other traversing strategies is inefficient even prohibitive because the total search space spanned by all available beam directions has been remarkably expanded. The authors in [4] considered such a situation where multiple systems shared a common 60GHz band, and a simple greedy algorithm was proposed to assign extra relaying links for the coexisted systems. Using the directional transmission, [5] proposed a spatial time slot scheduling algorithm to enhance the total throughput of the 60GHz relaying network. Although [6] evaluated the potential spatial reuse and degree of interference in a dense network, an efficient and practical solution of the joint beam adaptation in interference channel with 60GHz directional transmission has not been fully investigated.

In this paper, we propose a couple of adaptive BS algorithms based on the sequential stochastic approximation (SSA) with segmented indicator to solve the joint discrete optimization problem with emphasis on either better performance or lower complexity, respectively. Numerical simulation results are given to demonstrate the advantages on the efficiency and feasibility of the proposed SSA algorithms compared with the conventional ES method.

II. System model and problem formulation

A. Signal model

We consider a typical indoor communication scenario in which Q systems sharing 60GHz band are randomly located (see Fig.1). Each system comprises a pair of transceivers that are equipped with either directive steerable antenna or phased array. Although the systems are heterogenous, a center node is assumed as the controller to coordinate the beam directions in global. Equal transmit power is assigned for all systems since the power allocation is beyond the scope of this paper. For

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the Rx in system q, the baseband equivalent signal through the interference channel in discrete time is represented by

$$y_q[n] = \sum_{p=1}^{Q} h_{q,p}[n]x_p[n] + v_q[n], \quad q = 1, 2, \ldots, Q \tag{1}$$

where x_p is the transmit signal from system p and $h_{q,p}$ is the channel response between the Tx in system p and the Rx in system q. The additive noise v_q are independent identical distributed (i.i.d.) circular symmetric complex Gaussian random variables with zero mean and variance N_0. Due to the heterogeneous network, the signals from other systems are treated as unknown interferences, which limit the sum rate achieved in the network.

B. Ray-tracing based channel model

Ray-tracing technique is used in 60GHz channel model [7]. In this model, the transceivers are linked by the Line-of-Sight (LOS) or reflective rays that are clustered with their angular and temporal information predicted using the geometries. The near-optical channel can thus be modeled as

$$\begin{aligned} h(t, \phi_t, \theta_t, \phi_r, \theta_r) = \sum_i A^{(i)} C^{(i)}(t - T^{(i)}, \\ \phi_t - \Phi_t^{(i)}, \theta_t - \Theta_t^{(i)}, \phi_r - \Phi_r^{(i)}, \theta_r - \Theta_r^{(i)}) \end{aligned} \tag{2}$$

where $A^{(i)}$, $T^{(i)}$, $\Phi_t^{(i)}$, $\Theta_t^{(i)}$, $\Phi_r^{(i)}$, $\Theta_r^{(i)}$ are the amplitude, delay, departure and arrival angles (in azimuth ϕ and elevation θ) of cluster i, respectively, and

$$\begin{aligned} C^{(i)}(t, \phi_t, \theta_t, \phi_r, \theta_r) = \sum_k \alpha^{(i,k)} \delta(t - \tau^{(i,k)}) \\ \cdot\delta(\phi_t - \phi_t^{(i,k)})\delta(\theta_t - \theta_t^{(i,k)})\delta(\phi_r - \phi_r^{(i,k)})\delta(\theta_r - \theta_r^{(i,k)}) \end{aligned} \tag{3}$$

depicts the ray constitution of each cluster where $\alpha^{(i,k)}$, $\tau^{(i,k)}$, $\phi_t^{(i,k)}$, $\theta_t^{(i,k)}$, $\phi_r^{(i,k)}$, $\theta_r^{(i,k)}$ represent the same parameters for the kth ray as mentioned above. Without loss of generality, two-dimensional (2-D) ray-tracing is considered, namely, all the transceivers are located at same height and the clusters and rays travel within the same horizontal plane. Also, we assume that only the rays in LOS and up to the second order reflections finally contribute to the channel model.

C. Beambook

In general, a beambook covers the target radiation area by a collection of element beams with their main lobes pointing in different directions (see Fig.2). The beam switching (BS) algorithms try to find the best beams from the beambook for the transceivers by certain criteria. For instance, the multi-stage beam switching and steering (BST) algorithm used in WPAN standard requires beambooks with element beam patterns in different resolution levels. Here a generic 2-D pattern is empirically modeled by Gaussian decaying function [7] in horizontal plane as

$$G(\phi) = \begin{cases} G_0 \exp\left(-4\ln(2)\frac{\phi^2}{\phi_{-3dB}^2}\right) & : \quad |\phi| \le \frac{\phi_{ML}}{2} \\ G_{sl} & : \quad \text{else} \end{cases} \tag{4}$$

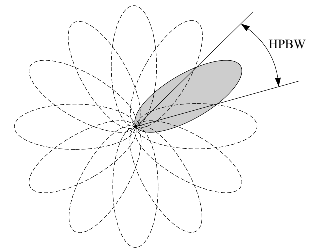

Fig. 2. A 2-D beambook and the uniformly partitioned radiation area at an interval of HPBW

in decibel, where

$$G_0 = 10\log\left\{\left(\frac{1.6162}{\sin(\phi_{-3dB}/2)}\right)^2\right\} \tag{5}$$

$$G_{sl} = -0.4111 \cdot \ln(\phi_{-3dB}) - 10.597 \tag{6}$$

are the empirical values of the maximum antenna gain and the side lobe antenna gain, respectively; ϕ_{ML} and ϕ_{-3dB} are the main lobe beam width and the half power beam width (HPWB) in azimuth angle. We assume that the element beams partition the radiation area evenly at an interval of HPBW, which is a good compromise between the number of partitions and the minimum antenna gain in each partition [7].

D. Problem formulation

Since the ray-traced channel in the fixed indoor propagation environment is usually assumed as semi-static during beamforming, the unique property of the directional transmission makes the link quality or sum rate solely depend on the chosen beam directions in each parallel system. More specifically, using a common beambook, denoted by $\mathcal{B}$, we define a beam selection vector, $\boldsymbol{\omega} = \{\omega_q\}_{q=1}^{Q}$ with $\omega_q = (b_{r,q}, b_{t,q})$, to indicate the indices of the selected partitions (or element beams) in the beambook for the transceivers in Q systems, i.e., $b_{r,q}, b_{t,q} \in \mathcal{B}$. The channel impulse response (CIR) between the Tx in system p and the Rx in system q can thus be represented by

$$h_{q,p}(t, \boldsymbol{\omega}) = \iint G(\phi_r, b_{r,q}) h(t, \phi_r, \phi_t) G(\phi_t, b_{t,p}) d\phi_t d\phi_r \tag{7}$$

for $p, q \in \{1, 2, \ldots, Q\}$ with zero elevation angles. Here $G(\phi, b)$ is the antenna gain if the main lobe is pointing to the bth direction defined in the beambook. Using (2) and (3) in (7), it is further simplified as

$$h_{q,p}(t, \boldsymbol{\omega}) = \sum_{\ell=1}^{N_{\text{rays}}} \beta_\ell(\omega)\delta(t - \tau_\ell) \tag{8}$$

where we aggregate all N_{rays} rays between the transceivers with the amplitudes and delays denoted by $\beta_\ell(\omega)$ and τ_ℓ, respectively. For the narrow band assumption, the differences in delay among the rays are negligible, then we have the flat-fading CIR defined as

$$\bar{h}_{q,p}(\boldsymbol{\omega}) \triangleq \sum_{\ell=1}^{N_{\text{rays}}} \beta_\ell(\boldsymbol{\omega}) \tag{9}$$

The sum rate for Q systems is altered solely by $\boldsymbol{\omega}$, that is

$$C_{\text{sum}}(\boldsymbol{\omega}) = \sum_{q=1}^{Q} \log_2(1 + \text{sinr}_q(\boldsymbol{\omega})) \tag{10}$$

where $\text{sinr}_q(\boldsymbol{\omega})$ is the signal to interference plus noise ratio (SINR) at the receiver in system q,

$$\text{sinr}_q(\boldsymbol{\omega}) = \frac{E_s|\bar{h}_{q,q}(\boldsymbol{\omega})|^2}{N_0 + \sum_{p=1,p\neq q}^{Q} E_s|\bar{h}_{q,p}(\boldsymbol{\omega})|^2} \tag{11}$$

where E_s and N_0 are the symbol energy and noise power density, respectively; $\bar{h}_{q,q}(\boldsymbol{\omega})$ refers to the communication channel within system q while $\bar{h}_{q,p}(\boldsymbol{\omega}), p \neq q$ are the channels interfered by other systems. For the purpose of analysis, we define an equivalent objective function without logarithm as

$$\Gamma(\boldsymbol{\omega}) = \prod_{q=1}^{Q}(1 + \text{sinr}_q(\boldsymbol{\omega})) \tag{12}$$

Therefore, to maximize the sum rate by determining the optimal beam directions $\boldsymbol{\omega}^* = \{(b_{r,q}^*, b_{t,q}^*)\}_{q=1}^{Q}$, we need to solve the following optimization problem

$$\boldsymbol{\omega}^* = \underset{b_{r,q}, b_{t,q} \in \mathcal{B}}{\arg\max}\, \Gamma(\boldsymbol{\omega}) \tag{13}$$

For such a joint discrete optimization problem, derivation of the optimal solution in closed-form seems prohibitive. Searching in brute force is simple and effective for single link, but it is impractical in our case because the total search space spanned by Q systems is extremely large even the multi-stage strategy is used. To improve the search efficiency, we resort to the stochastic approximation (SA) algorithm, which originated in operation research [8] and applied in MIMO antenna selection [9] and sensor network encoding [10].

III. Sequential stochastic approximation

In this section, we first apply the conventional two-stage BS scheme with ES strategy in the considered interference limited scenario, and then analyze the resulting complexity (or number of pilot transmissions) with imperfect channel estimation. After that, two adaptive BS algorithms based on the Sequential Stochastic Approximation (SSA) are proposed as the sub-optimal solutions with much lower complexity.

A. Exhaustive search (ES)

In two-stage BS, the best beams are found through two successive stages using beambooks with different resolution levels, namely, the sector-level and beam-level. In a cascading way, the total search space is remarkably reduced by confining the beam-level search within the sectors chosen in last stage. Suppose that the sector-level beambook contains $I = 4$ sectors with HPBW=90° and $J = 6$ fine beams with HPBW=15° constitute the individual beam-level beambook within each chosen sector. If the optimal beams (for Tx's and Rx's) are exhaustively searched for Q systems, the total search space is

$$C_{ES} = I^{2Q} + J^{2Q} \tag{14}$$

Apparently, the incurred complexity by ES is too high to implement even for a modest value of Q. For instance, $C_{ES} = 1745152$ for $Q = 4$ systems. In addition, the imperfect channel estimation usually requires repeated pilot transmissions in each trial, which further increases the resulting complexity.

B. Sequential stochastic approximation (SSA)

When the total search space is huge, searching for the global optimizer through ES is straightforward but inefficient even prohibitive. On the contrary, the sequential stochastic approximation (SSA) algorithm is an attractive solution because it plays well in compromising between performance and complexity. As mentioned, a large portion of complexity in the optimization lies on the objective function evaluations since the exact channel state information (CSI) is unavailable but only the noisy channel estimates. Without loss of generality, a narrow band pilot signal s with energy E_s is transmitted from the pth Tx using beam selection vector $\boldsymbol{\omega}$ for M times repeatedly and independently. The received signals at the qth Rx, denoted by $y_{q,p}^{(m)}, m = 1, \ldots, M$, are i.i.d random variables such that

$$y_{q,p}^{(m)}(\boldsymbol{\omega}) = \bar{h}_{q,p}(\boldsymbol{\omega})s + v_q^{(m)}, m = 1, 2, \ldots, M \tag{15}$$

where $\bar{h}_{q,p}(\boldsymbol{\omega})$ is the flat-fading CIR defined in (9) and $v_q^{(m)}$ refers to the noise with zero mean and power density N_0. Omitting $\boldsymbol{\omega}$ for clarity, an empirical average is derived by

$$\begin{aligned} \hat{y}_{q,p} &\triangleq \frac{1}{ME_s}\left\{y_{q,p}^{(1)H}y_{q,p}^{(2)} + y_{q,p}^{(2)H}y_{q,p}^{(3)} + \cdots + y_{q,p}^{(M)H}y_{q,p}^{(1)}\right\} \\ &= |\bar{h}_{q,p}|^2 + R_1 + R_2 \end{aligned} \tag{16}$$

where $(\cdot)^H$ is the conjugate transpose and the remaining

$$R_1 = \frac{1}{ME_s}\left\{2\text{Re}\{\bar{h}_{q,p}s\sum_{m=1}^{M} v_q^{(m)H}\}\right\} \tag{17}$$

$$R_2 = \frac{1}{ME_s}\left\{v_q^{(1)H}v_q^{(2)} + v_q^{(2)H}v_q^{(3)} + \ldots + v_q^{(M)H}v_q^{(1)}\right\} \tag{18}$$

are random variables with zero mean. By the law of large number, we know that $\hat{y}_{q,p}(\boldsymbol{\omega}) \to |\bar{h}_{q,p}(\boldsymbol{\omega})|^2$ if $M \to \infty$. Therefore, the objective function in (12) can be estimated based on these unbiased channel measurements $\hat{y}_{q,p}(\boldsymbol{\omega})$ using (16) and (11) as

$$\hat{\gamma}(\boldsymbol{\omega}) = \prod_{q=1}^{Q}\left(1 + \frac{E_s\hat{y}_{q,q}(\boldsymbol{\omega})}{N_0 + \sum_{p=1,p\neq q}^{Q} E_s\hat{y}_{q,p}(\boldsymbol{\omega})}\right) \tag{19}$$

Using the estimated objective function, we can implement the SSA based BS algorithms with two searching strategies: *two-stage* (sector & beam level, SBL) for a reduced total search space but limited sum rate or *beam-level (BL) only* for an enhanced performance at the cost of increased complexity.

1) SSA algorithm with segmented indicator: The standard SA algorithm [8] usually maintains indicators for all states in the search space, which finally guarantee the global optimality. To reduce the storage cost incurred by the huge search space encountered in this paper, the proposed BS algorithms keep the indicators K and Σ in local segments corresponding to the Tx-Rx beam combinations within each system, where the entries in $K \in \mathbb{N}^{Q\times P}$ and $\Sigma \in \mathbb{R}^{Q\times P}$ indicate the number of visits and the accumulated objective function for each local beam combination, respectively; and $P = I^2$ or J^2 is the length of each segment in sector or beam stage. The SSA algorithm with segmented indicator is summarized in Algorithm 1.

Algorithm 1 Sequential SA with segmented indicator

STEP 0: INITIALIZATION
Set n=0 and prepare the beambook $\mathcal{B}$ for sector/beam level;
Choose initial directions $\boldsymbol{\omega}^{(0)} = \{\omega_q^{(0)}\}_{q=1}^{Q}$ with $\omega_q^{(0)} \in \mathcal{B}^2$ uniformly, and reset K and Σ;
STEP 1: SAMPLING AND EVALUATION
FOR n=1,2,...
  FOR q=1,2,...,Q
    Generate $\tilde{\boldsymbol{\omega}}^{(n)}$ from $\boldsymbol{\omega}^{(n)}$ by replacing its qth element with another random selection, i.e., $\tilde{\omega}_q^{(n)} \neq \omega_q^{(n)}$;
    Estimate $\hat{\gamma}(\boldsymbol{\omega}^{(n)})$ and $\hat{\gamma}(\tilde{\boldsymbol{\omega}}^{(n)})$ using (19);
STEP 2: ACCUMULATION AND UPDATE
    $K(q,\tilde{i}) = K(q,\tilde{i}) + 1; \quad \Sigma(q,\tilde{i}) = \Sigma(q,\tilde{i}) + \hat{\gamma}(\tilde{\boldsymbol{\omega}}^{(n)})$
    $K(q,i) = K(q,i) + 1; \quad \Sigma(q,i) = \Sigma(q,i) + \hat{\gamma}(\boldsymbol{\omega}^{(n)})$
    where i and $\tilde{i}$ are the linear indices of $\omega_q^{(n)}$ and $\tilde{\omega}_q^{(n)}$;
STEP 3: DECISION
    If $\frac{\Sigma(q,\tilde{i})}{K(q,\tilde{i})} > \frac{\Sigma(q,i)}{K(q,i)}$, then perform $\omega_q^{(n+1)} = \tilde{\omega}_q^{(n)}$;
    otherwise, perform $\omega_q^{(n+1)} = \omega_q^{(n)}$.
  ENDFOR
  Gather $\boldsymbol{\omega}^{(n+1)} = \{\omega_1^{(n+1)}, \omega_2^{(n+1)}, \ldots, \omega_Q^{(n+1)}\}$
ENDFOR

2) SSA+SBL: When the proposed SSA algorithm is implemented in two-stage or sector and beam level (SBL) search, the best sections are first found as described in Algorithm 1 using sector-level beambook, and then the best beams are found by re-launching the same procedures using the beam-level beambooks that split the chosen sectors into high resolution beams. Applying SSA instead of ES in such a cascading way, the implementation complexity is remarkably reduced because of the shrunk search space and the adaptive searching strategy within each level. However, the global optimality is not guaranteed because of the non-global indicators and the error dispersion among different levels.

3) SSA+BL: If the mentioned multi-level beambook is not supported, another variant algorithm (SSA+BL) performs direct search in beam-level (BL) using a "thicker" beambook covering the whole radiation area uniformly. Compared with SSA+SBL, SSA+BL requires more iterations to search within an expanded search space, but an enhanced performance is also expected thanks to the high resolution beam pattern and free of error dispersion. In practical 60GHz scenario, the LOS directions (if available), in which the beams are steered to their desired devices, can be measured offline. Although they might not be optimal, such prior information probably offers a *Hot Start* (HS) that helps SSA+BL start from a good initial state instead of a random selection.

TABLE I
BASIC SIMULATION PARAMETERS

Parameters	Values
Carrier frequency (f_0)	60GHz
Transmit power (P_t)	10dBm
Noise figure (NF)	7dB
Implementation loss (L_I)	5dB
Reflection loss (L_r)	2dB
SINR threshold	5.5dB
Number of independent drops (N_{drop})	100
HPBW of sectors (ϕ_{-3dB})	90°
Number of sectors (I)	4
HPBW of beams (ϕ_{-3dB})	15°
Number of beams in a sector (J)	9
Number of CE per trail (M)	10

TABLE II
DATA RATE AT SINR THRESHOLD

MCS	1	2	3
Data rate (Gbps)	0.952	1.904	3.807
SINR threshold (dB)	5.5	13	18

IV. NUMERICAL SIMULATIONS

In following simulations, a typical indoor communication scenario with dimensions 8m(L)×6m(W) is considered. In this room, Q systems and their transceivers are located on a same horizontal plane at height 1m. The basic simulation parameters are listed in Table.I, and Table.II lists the achievable data rate for single link given a proper modulation and coding scheme (MCS) at different SINR levels. The concerned metrics, i.e. sum rate, number of pilot transmissions and active links, are evaluated by averaging over 100 drops. In each drop, all transceivers are placed randomly and independently, and the rays between the transceivers are then generated with the parameters predicted by 2-D ray-tracing technique [7]. The flat-fading CIR's between the transceivers are finally gathered thereby. The proposed SSA algorithms are convergent and terminated when a sector or beam combination is chosen repeatedly in 1000 consecutive iterations, or enough iterations are elapsed. In addition, the ES is evaluated only for $Q = 1, 2, 3$ because the total search space is too huge to find the global optimizer in brute force for a larger Q.

Fig.3 compares the mentioned schemes in the sense of the average sum rate conveyed by up to $Q = 8$ systems over 100 drops for each Q while Fig.4 and Fig.5 display the average number of pilot transmissions (or CE's) and active links (with positive rate) resulted in the same simulation, respectively. When $Q < 3$, the conventional ES algorithm with two-stage strategy has the optimal sum rate and spatial reuse performance as well as affordable complexity. But the performance evaluation becomes prohibitive for a larger Q because of the

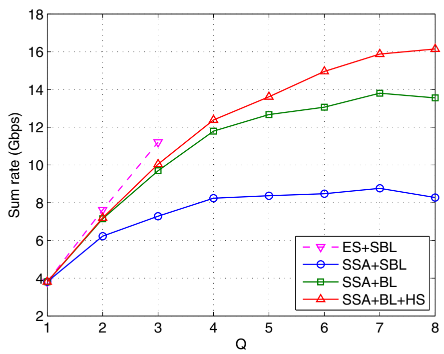

Fig. 3. Sum rate vs. number of parallel systems

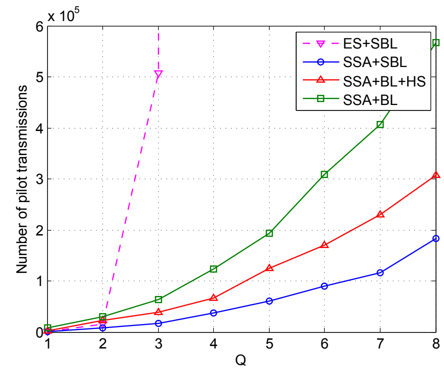

Fig. 4. Number of pilot transmissions vs. number of parallel systems

explosive number of the required pilot transmissions.

For the proposed SSA algorithm with SBL, the cascading beam adaptation achieves more than half of optimal performance by ES with comparable amount of complexity when Q is small. The metrics of sum rate and the number of active links are increasing as Q is getting large, and the increasement is shrinking when the network is crowded. One explanation is that the expanded search space makes the adaptive algorithms slow in convergence and thereby difficult to reach the global optimizer in each level before the termination condition is met. The other is that the error occurred in sector-level is probably dispersed in beam-level, which limits the quality of the final beam selection. The severe interference among the transceivers in this case also limits the achieved performance in fundamental. Although only sub-optimal solutions can be guaranteed, the remarkably reduced complexity, compared with ES, highlights the efficiency and feasibility of the proposed adaptive BS algorithms.

The direct BS algorithm in beam-level only (SSA+BL) outperforms the cascading search in SBL in both metrics with higher complexity (i.e. the required number of pilot transmissions). Using a beambook with higher resolution element beams, the total search space is further expanded, but a better solution can be found without error dispersion given enough number of iterations. Similarly, such an advantage in spatial reuse factor is also conspicuous at a cost of extra complexity.

In aid of the prior information, SSA+BL+HS obtains slight performance enhancements in both sum rate and spatial reuse factor on the basis of the pure beam-level search (SSA+BL), and more than one third of the complexity is saved. This is achieved by a hot start that offers a good initial state rather than a random start, which implies that the SSA+BL+HS is indeed an efficient solution that plays well in balancing between performance and complexity in practice.

V. Conclusions

Adaptive BS algorithms based on SSA with segmented indicator are proposed to determine the (sub-)optimal beam directions for Q coexisted systems in 60GHz interference channel. When implemented in a dense network, they are preeminent and practical because they are more efficient in

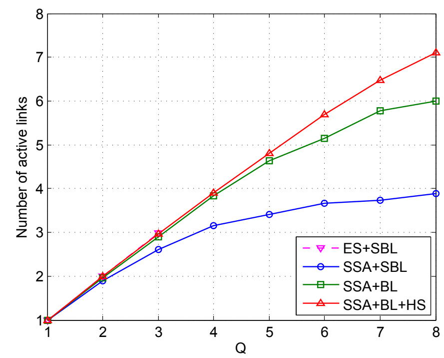

Fig. 5. Number of active links vs. number of parallel systems

computation than the conventional ES and more economic in storage than using the standard SA, especially when the prior information is available. Numerical simulations show that the proposed joint beam adaptation algorithms achieve decent performances with affordable complexity even in the dense network while the ES is definitely prohibitive in this case.

References

[1] IEEE 802.15 WPAN Millimeter-wave Alternative Task Group 3c (TG3c). url:http://www.ieee802.org/15/pub/TG3c.html
[2] R. Etkin, A. Parekh and D. Tse, "Spectrum sharing for unlicensed bands", *IEEE J. Sel. Areas Commun.*, vol.25, no.3, pp.517-528, April 2007
[3] X. An, C-S Sum, R.V. Prasad, *et al.*, "Beam switching support to resolve link-blockage problem in 60 GHz WPANs", in *Proc. PIMRC 2009*, pp.390-394, 13-16 Sept. 2009
[4] C. Yiu, S. Singh, "Link Selection for Point-to-Point 60GHz Networks", in *Proc. IEEE ICC 2010*, pp.1-6, 23-27 May, 2010
[5] Z. Lan, J. Wang, J. Gao, *et al*, "Directional Relay with Spatial Time Slot Scheduling for mmWave WPAN Systems", in *Proc. IEEE VTC 2010-Spring*, pp.1-5, 16-19 May, 2010
[6] M. Park, P. Gopalakrishnan, "Analysis on spatial reuse and interference in 60-GHz wireless networks", *IEEE J. Sel. Areas Commun.*, vol.27, no.8, pp.1443-1452, October 2009
[7] A. Maltsev *et al.*, "Channel Models for 60 GHz WLAN Systems", *IEEE* 802.11-09/0334r8, 2010.
[8] S. Andradottir, "Aglobal search method for discrete stochastic optimization", *SIAM J. Optimiz.*, vol. 6, no. 2, pp. 513-530, May 1996
[9] K. Dong, N. Prasad, X. Wang and S. Zhu, "Adaptive antenna selection and Tx/Rx beamforming for large-scale MIMO systems in 60 GHz channels", *EURASIP J. Wirel. Comm.*, 2011:59.
[10] I. S. Jang and X. Wang, "Discrete stochastic approximation algorithms for design of optimal sensor fusion rules", *Int. J. Sensor Networks*, Vol. 2, Nos. 3/4, 2007