MOBILITY ENHANCED SMART ANTENNA ADAPTIVE SECTORING FOR UPLINK CAPACITY MAXIMIZATION IN CDMA CELLULAR NETWORK

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ABSTRACT

In this paper, adaptive sectoring of a CDMA cellular network is investigated, and the aim is to maximize the uplink capacity by utilizing mobiles' spatial information. The distribution of mobiles is modeled as a spatial Poisson process, whose rate function quantizes mobiles' concentration and which can be inferred with a Bayesian estimator based on network traffic. The time dynamics of the rate function is assumed to evolve according to mobiles' mobility pattern and which is formulated using the Influence model. With mobiles' spatial distribution, the interference and thus the outage probability of different sector partitions of a cell can be computed. The adaptive sectoring problem is formulated as a shortest path problem, and the optimal path corresponds to the sector partition with the minimum outage probability.

1. INTRODUCTION

It is well known that CDMA systems are interference limited, and sectoring has been an effective mean of increasing the network capacity by introducing spatial domain orthogonalization to the system. The conventional method applied in, for example, GSM and IS-95 employs 120° or 60° sectoring to achieve better reuse of network resources. However, one major drawback of this scheme is its inflexibility when dealing with non-stationary and non-uniform mobile distribution. For example, hot spots can cause outage in a sector while other sectors have light traffic.

In this paper, we extend the conventional sectorization by allowing base stations to observe the network traffic and adaptively sectorize the cell accordingly. The dynamic sectorization is achieved by the deployment of smart antenna system at the base station. While smart antenna is often associated with adaptive beam forming, our approach is fundamentally different. Even though both approaches utilize the spatial domain, while beam forming directs dedicated beam to each mobile, sectorization spans the cell with few main beams with each beam corresponds to a sector.

Many papers, [1, 2, 3], have looked into this adaptive sectoring problem. [1] deals with the problem when mobiles' locations within the network are known and stationary, such as the case in wireless local loop. The adaptive sectoring is solved for two cases: minimizing the total transmit power of the mobiles and minimizing the total received power at the base station. [3] assumes a spatial Poisson process with the intensity function λ, which is assumed known, and the probability of having k mobiles in an area A is given by the Poisson distribution $P(k, A) = \frac{(\lambda A)^k}{k!} e^{-\lambda A}$. By fixing k and $P = \sum_{j=k}^{\infty} P(j, A)$, and replace A by $\frac{r^2\theta}{2}$ where r is the cell radius and θ is the sector's angle span, P is the probability of having more than k users in θ. Adaptive sectoring is computed by an iterative method which reduces θ when k is above a certain threshold. [2] continuously monitors the SINR (signal to interference and noise ratio) of all the users, and sectorizes the cell to equalize the SINR in all sectors. However, in each of the above solutions, there are certain limitations. While the work in [1] is designed to work for wireless local loop, it is difficult to extend it for constantly moving mobiles. In [3], the success of the algorithm depends on the knowledge of the mobile concentration. Moreover, the SINR-based sectoring in [2] may be unstable because of the shadowing and fast fading in the measurement of SINR [4].

The major difference between adaptive and conventional sectoring is the system's responsiveness to changes in mobile distribution. In [5], movement of people are observed to follow certain patterns. However, mobility is not observable, it can only be indirectly observed from the network traffic. In this paper, a mobility-enhanced traffic model is developed to capture mobile distribution changes over period of a day from the network traffic observed. Based on the estimated mobile distribution, the sectoring problem is solved to maximize the uplink capacity.

The paper is organized as follows. Sec. 2 formulates the adaptive sectoring problem and defines the related models. Sec. 3 develops the mobility model underlying the adaptive sectoring problem. Sec. 4 presents the simulation results and Sec. 5 concludes the paper.

2. ADAPTIVE SECTORING PROBLEM FORMULATION

In this section, the aim is to formulate the adaptive sectoring as a minimization problem of outage probability in CDMA uplink. In order to compute the outage probability at a sector, the knowledge of mobiles' whereabouts is necessary. Yet, as the density of mobiles increases, tracking individuals is too computationally intensive, and may lead to frequent sectoring because of various individual movement patterns. As a result, the algorithm developed concentrates on the statistics of mobiles instead. The network is modeled as a hexagonal cellular network, with each cell consists of six equally spaced areas called *subareas*, and statistics of mobiles is collected with respect to each subarea in order to infer the concentration of mobiles. Mobiles are assumed to be distributed as a spatial Poisson process, and its rate function is uniform in each subarea; in this section, the rate function is assumed known, the estimation problem is discussed in the next section. Each base station collects statistics in its subareas, and shares it among its neighboring base stations. The sharing of mobiles' spatial information allows, as demonstrated later, the computation of the outage probability.

From the above discussion, the sectoring considered in this paper is discrete sectoring in terms of subareas. Specifically, each sec-

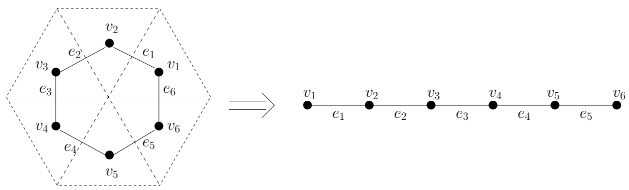

Fig. 1. The Graph-theoretic representation of a hexagonal cell where the cell is divided into six equally spaced areas called *subareas*. The graph on the left is the ring representation of a cell, where each node is a subarea. (Sectors are disjoint subsets of nodes.) The graph on the right is one of six reduced string representations, where the edge e_6 is arbitrarily chosen and removed.

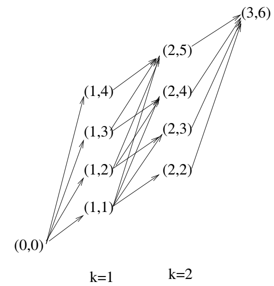

Fig. 2. Acyclic network generated from the string illustrated in Fig. 1.

tor in a cell is defined by the beam pattern of the base station's sector-beam, whose beamwidth is multiples of a subarea's angular span. In addition, perfect beam pattern is assumed; there is no overlap between beams and thus mutual interference is ignored. As a result, given the mobile statistics in the subareas, the outage probability experienced at a sector can be computed and which will be used as the cost weighting different sectoring decisions. Note that the dimension of the subarea defines the granularity of the model; the smaller the subarea, the finer the tracking of the mobile distribution and also the sectoring, but the higher the computational load on the system to perform estimation.

2.1. Adaptive Sectoring As Graph Partitioning

A natural mathematical representation of the adaptive sectoring problem is graph partitioning. The key advantage of such representation is that, under certain conditions, the graph partitioning problem has a one-to-one correspondence to a shortest path problem, and which is readily solvable using Dijkstra's algorithm. (The method was first applied in [1] to sectorize wireless local loops with stationary mobiles.) In this subsection, the graph partitioning formulation of the adaptive sectoring problem is demonstrated.

Fig. 1 illustrates the graph theoretical representation of the cellular network. A cell is modeled as a ring of nodes where each node represents a subarea. Let the graph $G = (V, E)$ denotes the ring and the vector $V = \{v_1, v_2, \ldots, v_6\}$ denotes the nodes, the sectoring problem is equivalent to the partitioning of nodes (subareas) into subsets (sectors). Let $\pi = \{S_1, \ldots, S_N\}$ be a partition of the nodes, where the subgraph induced by S_i for $i = 1, \ldots, N$ is connected, the cost function of the partition π is measured by the summation of weights $W(S_i)$ for all i, where $W(S_i)$ is the outage probability experienced in the corresponding sector of S_i. Specifically, the graph partitioning problem is to find a partition which minimize the following cost

$$\min_{\pi} C(\pi) = \sum_{i=1}^{N} W(S_i). \tag{1}$$

In general, the problem of optimally partitioning an arbitrary graph with an arbitrary cost function is NP-hard. However, it has been shown that the partitioning problem can be solved in polynomial time if the graph is a *string* and the cost function is *separable*. The important observation of our ring of subareas is that it can be broken into a string if an edge is removed. Given the string, the partitioning problem can be mapped to an equivalent shortest path problem [6]. Fig. 2 demonstrates the acyclic network constructed corresponding to its partitioning problem counterpart in Fig. 1; the weight of each edge in the acyclic network is calculated by $W(S_i)$. Details of the construction can be found in [1]. It should be noted that the removal of an edge traded problem complexity with computational complexity since six strings are generated from one ring.

The computation of $W(S_i)$, i.e., the outage probability, is based on the evaluation of $P(I^i + I^o > \alpha)$, where I^i and I^o are in-cell and other-cell interference respectively, and α is the maximum total interference the system can handle. Because the mobiles are modeled as a spatial Poisson process, and the rate functions of the process in each subarea is assumed known, also assuming soft hand-off, log-normal shadow loss and perfect power control, the in-cell and other-cell interference can be computed by separating the spatial Poisson process into two processes using the Marking theorem and computing their corresponding signal power at the base station of interest. The two processes are referred to as the in-cell mobiles and the other-cell mobiles: the in-cell mobiles is the spatial Poisson marked by the probability that the mobile is power controlled by the base station of interest and the other-cell mobiles is marked by the probability that the mobile is not power controlled by the base station of interest. The calculation of outage probability with Poisson field has been studied in many papers, and the result we adopted is studied in [7]. The outage probability can be numerically evaluated based on the following equation:

$$P(I^i + I^o > \alpha | I^i > 0) = \frac{e^{-m}}{1 - e^{-m}} \sum_{j=1}^{\infty} \frac{m^j}{j!} Q(\tilde{y_j}) \tag{2}$$

where $\tilde{y_j} \equiv (\alpha - j + 1 - \kappa_1)/\sqrt{\kappa_2}$, κ_1 and κ_2 are the mean and variance of the other-cell Poisson process respectively, m is the mean of in-cell Poisson process and Q is the Q-function for the standard normal distribution.

3. MOBILITY MODEL

From the previous section, the adaptive sectoring problem is shown to be equivalent to a shortest path problem and whose weight is a function of a spatial Poisson process. In order to compute the optimal sectoring, estimation of the spatial Poisson's rate function is necessary. Once the weight of each edge in the acyclic network is determined, Dijstra's algorithm can be used to compute the optimal sectoring. (Description of Dijstra's algorithm is omitted since plenty of literatures is available.) In this section, the justification of the spatial Poisson process is described and a MAP estimator of its rate function is developed.

3.1. Mobility-Enhanced Traffic Model

In general, mobiles' mobility pattern is not observable, and it can only be indirectly observed through the network traffic processed at the base station. The approach taken is inspired by [7] where the mobile distribution is modeled as a spatial Poisson process and its relation to the network traffic is demonstrated with the following theorem.

THEOREM 1 Let Π_t be a Poisson process of arriving calls at a base station with constant rate of X_k from mobiles in an arbitrary subarea. Once the mobiles placed the call, they move at random around the subarea with independent trajectories. Let E be a spatial subset of the subarea such that the probability of the mobile who called at time s being in E at a subsequent time t is $p(s,t)$. Then the number of mobiles in E at time t has a Poisson distribution with mean

$$u(t) = \int_0^t X_k \, p(s,t) ds.$$

Assuming uniform distribution for $p(s,t)$ over the subarea, the distribution of the mobiles in the subarea is a spatial Poisson process with rate equals to that of the arriving calls.

PROOF The proof can be found in [8], (pg 49 Bartlett's Theorem). ∎

In Theorem 1, a number of assumptions are made, and it is worthwhile to go into the details.

Assumption 1: The arrival process at the base station is a Poisson process with constant rate. The arrival process referred to in the Theorem is the connection requests made by mobiles in the subarea. For example, the number of times Access Channel is requested in IS-95 or CDMA2000. From the study of broadband network traffic [9], the connection request is generally modeled as an inhomogeneous Poisson process. The additional assumption on the constant rate is justified by assuming the rate to be a slowly varying process which has finite states and jumps on a hourly basis.

Assumption 2: The uniform probability distribution over the subarea. The assumption is made to simplify the discussion, and it seems reasonable if the subarea is small enough such that highly attractive locations such as shopping malls does not appear like a clustered point in the subarea. However, other distributions may be applied but they are not studied in this paper.

The advantages of relating the network traffic to a spatial Poisson process are 1) The time dynamics of the connection requests in each subarea can be described by the mobiles' mobility pattern. 2) The rate function of the spatial Poisson process can be estimated in real time from the statistics of connection requests.

Model Definition

Let $i = 1, 2, \ldots, M$ denotes subareas, where M is the number of subareas in the network, and $k = 0, 1, \ldots, 23$ denotes hours of a day, Π_k^i is the spatial Poisson process with constant rate X_k^i in subarea i during the time interval $[k, k+1)$. $X_k = [X_k^1, X_k^2, \ldots, X_k^M]$ is a discrete time discrete state stochastic process, and, with Theorem 1, its state controls the rate of connection arrivals observed in each subarea. If there is only one subarea, X_k^1 is a hidden Markov chain observed through a Poisson process. For M subareas, the state of X_k^i for all subarea i is modeled with the Influence model [10]. Suppose the subarea of interest is i, let $D(i)$ denotes the dependency of i, the transition probability for X_k^i is

$$P(X_{k+1}^i | X_k^1, \ldots, X_k^M) = \sum_{j \in D(i)} d_{ij} P(X_{k+1}^i | X_k^j), \qquad (3)$$

where $D(i)$ refers to i itself and its adjacent subareas, and d_{ij} and $P(X_{k+1}^i | X_k^j)$ are model parameters which are assumed known. (Some parameter estimation techniques can be found in [11, 12].) Furthermore, the initial probability distribution $P(X_{k=0}^i)$ is also assumed known for all i.

3.2. MAP Estimator of Spatial Poisson's Rate Function

In this subsection, the maximum a posteriori estimator of X_k^i given the connection requests statistics is introduced. (The derivation is omitted.) Since the estimators for all subareas are equivalent, and for notational convenience, the subarea to be estimated is labeled as X_k^1, and whose closest neighbors are labeled as X_k^2, X_k^3 and X_k^4. Only 3 closest neighbors are considered because hexagonal cells of six subareas are assumed.

Let Π_k^1 be a spatial Poisson process with rate X_k^1 at the subarea 1, and let $\{N_k^1(\sigma); k \le \sigma < t\}$ denotes the observed path of Π_k^1 in the time interval $[k, t)$, i.e., the connection requests processed at the base station. The a posteriori probability mass function of X_k^1, $P(X_k^1 | N_k^1(\sigma); k \le \sigma < t)$, is tracked as time t progresses based on the following algorithm.

For $t \in [k, k+1)$, define $\triangle N_t^1 = N_k^1(t + \triangle t) - N_k^1(t)$, where $\triangle t$ is an arbitrary time interval, the a posteriori probability mass function evolves according to

$$\begin{aligned} &P(X_k^1 | N_k^1(\sigma); k \le \sigma < t + \triangle t) \\ &= P(X_k^1 | N_k^1(\sigma); k \le \sigma < t)\{1 + \\ &(X_k^1 - \bar{X}_k^1)\bar{X}_k^{1^{-1}}(\triangle N_t^1 - \bar{X}_k^1 \triangle t)\} + o(\triangle t), \end{aligned} \qquad (4)$$

where $\bar{X}_k^1 = \sum_{X_k^1} X_k^1 P(X_k^1 | N_k^1(\sigma); k \le \sigma < t)$. For $\triangle t$ small enough, $\triangle N_t^1$ is either 0 or 1 depending on occurrence or nonoccurrence of events and $o(\triangle t)$ is negligible. At the end of the time interval $[k, k+1)$, label $n_1 = \{N_k^1(\sigma); k \le \sigma < k+1\}$, $n_2 = \{N_k^2(\sigma); k \le \sigma < k+1\}, \ldots$, and $n_4 = \{N_k^4(\sigma); k \le \sigma < k+1\}$, the probability mass function of the subarea 1 at the beginning of the next time interval $[k+1, k+2)$ is

$$\begin{aligned} &P(X_{k+1}^1 = x | n_1, n_2, n_3, n_4) \\ &= \textstyle\sum_{j=1}^4 d_{1j} \sum_{X_k^j} P(X_{k+1}^1 = x | X_k^j) P(X_k^j | n_j), \end{aligned} \qquad (5)$$

where d_{1j} and $P(X_{k+1}^1 | X_k^j)$ are Influence model parameters. For $t \in [k+1, k+2)$, (4) again continuously update the a posteriori probability upon receiving connection requests. As a result, assuming the initial probability $P(X_{k=0}^i)$ is known for all i, the a posteriori probability of X_k^i can be tracked for any time t, and thus the MAP estimator at time t is

$$\arg\max_x P(X_k^1 = x | N_k^1(\sigma), \ldots, N_k^4(\sigma); k \le \sigma < t) \qquad (6)$$

4. SIMULATION OF ADAPTIVE SECTORIZATION

The typical problem of nonuniform traffic is manifested in the generation of hot spots. In this section, the response of the adaptive sectoring algorithm is studied against a hot spot scenario, where a comparison in network capacity of the adaptive and the fixed sectoring is made. The network consists of 19 cells and each cell has radius of one. The value of the path-loss exponent, γ, is assumed to be 4, and the required SIR is set to 7 dB/128, which corresponds to a despread SIR of 7 dB when the spreading factor is 128. Furthermore, the shadowing component in the propagation uncertainty is taken to have standard deviation of 8 dB.

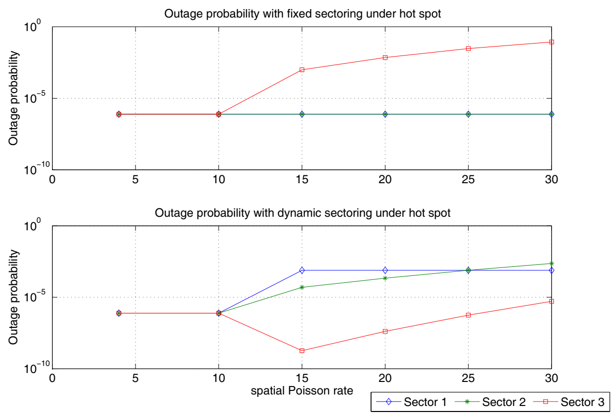

Fig. 3. Comparison of system performance with fixed and dynamic sectoring under hot spot condition. It can be observed that dynamic sectoring balances the traffic and keep the outage probabilities of the three sectors under 1%, where the loaded sector in fixed sectoring has approximately 9% outage probability.

Suppose the cell of interest is the central cell, the hot spot scenario considered is to increase the rate function of its two neighboring cells, and determine how adaptive sectoring can mitigate the effect. Fig. 3 illustrates the difference in outage probabilities between the fixed and the adaptive sectoring. In the fixed sectoring case, when the rate function is gradually increased, the sector closest to the hot spot experiences high outage probability while the other two sectors have all the unutilized resources. On the other hand, the adaptive sectoring algorithm narrows the loaded sector when its outage probability starts to rise, and share the load among the three sectors. It is observed that even though the outage probabilities have risen in the other two sectors, they are well below 1%; the outage probability in the fixed sectoring case has soared to approximately 9%.

5. CONCLUSION

In this paper, the adaptive sectoring problem is formulated as a shortest path problem. The weight matrix of the shortest path problem depends on mobiles' spatial distribution over the network, and which is estimated by a MAP estimator based on the network traffic processed at base stations. The real time tracking of the network traffic enables the system to respond to non-stationary and non-uniform mobile distribution; the effect of mobile distribution is measured by the outage probability it imposes on the system, and adaptive sectoring is implemented to minimize it. The simulation of hot spot scenario has demonstrated how adaptive sectoring cope with nonuniform traffic; the load is balanced between sectors such that no sector has outage probability exceeding 1%, while the fixed sectoring scheme experiences outage of approximately 9%.

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