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Bio-Inspired Uplink Power Control for Energy-Efficient Mobile Stations in Wireless Cellular Networks

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Abstract

In this paper, we propose a distributed uplink power-control algorithm inspired by the flocking behavior in birds as a means of improving the energy efficiency of mobile stations (MSs) in a wireless cellular network. Just as each bird in a flock attempts to match its velocity with the average velocity of the adjacent birds, in the proposed algorithm, each MS in a cell matches its uplink rate with the average uplink rate of the co-channel MSs in adjacent cells by controlling its transmission power. Simulation results show that the proposed power-control algorithm effectively reduces the power consumption in the MS, while maintaining a low outage probability, which eventually improves the energy efficiency of the MS.

Key Words: Uplink power control, Bio-inspired algorithm, Energy-efficient network, Flocking model

1. Introduction

It is very important to reduce the energy consumption of mobile stations (MSs) in cellular networks because MSs use battery power and their lifetimes significantly influence the experience of the users. Most of the power is consumed in the radio frequency amplifier during the uplink transmission; hence, reduction of uplink power can prolong the lifetime of the MS [1]. Therefore, in this paper, we propose an uplink power-control algorithm to reduce the energy consumption of MSs, while guaranteeing the quality of service of the uplink transmission in wireless cellular networks.

To control the transmission power of the MS in each cell in a distributed manner, we try to apply the biological phenomenon known as *flocking behavior*, which is exhibited when a group (or flock) of birds flies together [2]. Because of the similarities between the flocking behavior and power control in a cellular network, we make use of the underlying principles of flocking behavior in our uplink power-control algorithm. Just as the flocking algorithm operates in a simple and distributed manner and shows convergent phenomena, our proposed bio-inspired uplink power-control algorithm operates with a low level of complexity without a centralized controller and shows that the rates of the MSs converge to the same value, which maximizes the minimum rate. This leads to a decrease in both the outage probability and energy consumption of the MS and eventually improves the energy efficiency of the MS in the wireless cellular network.

2. System Model

We consider a cellular network consisting of N cells. We assume that each channel is allocated to a certain MS in each cell by an arbitrary user scheduling method; thus, the number of MSs using the same channel (i.e., co-channel MSs) becomes N [3]. MS i is served by the base station (BS) i. P_i denotes the transmit power of MS i and n_i denotes the noise power at BS i. G_{ij} denotes the channel gain of the communication link from MS j to BS i. This system model for a two-cell case is illustrated in Fig. 1.

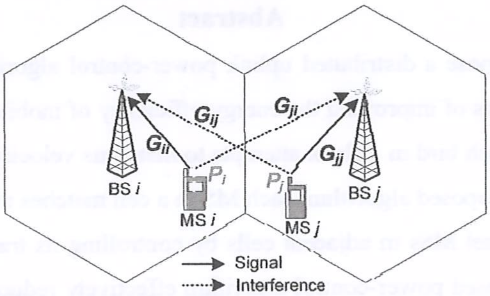

Fig. 1. System model for the two-cell case.

Now, the signal-to-interference-plus-noise ratio (SINR) of MS i is expressed as

$$\gamma_i = \frac{G_{ii}P_i}{\sum_{j=1,j\neq i}^{N} G_{ij}P_j + n_i}, \quad 1 \le i \le N, \tag{2.1}$$

From Shannon's theorem, the bit rate of MS i per unit bandwidth is given by

$$R_i = \log_2(1+\gamma_i) \quad \text{[b/s/Hz]} \tag{2.2}$$

In addition, we define the outage probability of MS i to be the probability that the received SINR γ_i falls below the required SINR, γ_{req}, which is given by

$$Q_i := \Pr\{\gamma_i < \gamma_{req}\}. \tag{2.3}$$

Finally, we define the energy efficiency of MS i as the number of information bits transmitted without error per unit bandwidth and per unit energy. Because the occurrence of outage induces bit errors, the energy efficiency is defined as [1]:

$$E_i := \frac{(1-Q_i)R_i}{P_i} \quad \text{[b/Hz/J]} \tag{2.4}$$

3. Proposed Bio-Inspired Uplink Power-Control Algorithm

In a flock of birds, the state of the flock converges to one in which all birds fly at the same velocity. The simple rule governing this flocking behavior is that each bird autonomously adjusts its velocity according to the velocities of its neighbors, and this is explained by the representative Cucker–Smale flocking model. In other words, at time t, each bird i adjusts its velocity v_i as follows: [2]

$$v_i(t+1) - v_i(t) = \frac{\lambda}{N} \sum_{j=1}^{N} \psi(|x_j - x_i|)(v_j(t) - v_i(t)) \tag{3.1}$$

where N is the number of birds, $\lambda \leq 1$ is the coupling strength used as a learning parameter, and x_i is the position of the bird i. ψ denotes a communication range function depending on the distance between two birds. For example, it is defined as $\psi(|x_j - x_i|) = 1$ only if $|x_j - x_i| \leq r$, where r is the visible range of a bird. In this case, the flocking model can be interpreted as a local-averaging algorithm for bird velocity. It is also well-known that this flocking algorithm is the best method for a flock of birds to arrive at its destination as quickly as possible without stragglers when aerodynamic interactions exist among the birds. Therefore, this flocking algorithm, which makes all the birds in the flock fly at the same velocity, eventually maximizes the minimum speed of the flock and reduces its energy consumption.

Just as all birds in a flock match their velocities to the same value while maximizing the minimum bird speed in an aerodynamic interactive environment, our proposed power-control algorithm is designed to make the uplink rates of all the MSs the same, which eventually maximizes the minimum rate of the MSs in an inter-cell interference environment. Therefore, the proposed algorithm controls the transmit power of each MS in such a way as to equalize the uplink rates of all MSs. Because the rate of MS i is related to the transmit powers of all the other MSs as well as to its own transmit power, controlling the transmit power of one MS influences the rates of all other MSs; iterations are therefore required to obtain the final equal rate value just as in the flocking algorithm. At each step, each MS recognizes the uplink rate information of the other MSs, from the header information broadcast by its neighboring BSs, and sets its next target rate to the average of the recognized rate values, just as each bird in a flock adjusts its velocity to the average velocity of its neighbors. Thereafter, the MS determines its transmit power to achieve this target rate individually. This distributed local rate-averaging operation is repeated until the target rate does not change any more (i.e., until all the MS rates converge to the same value).

The operational procedure of the proposed power-control algorithm follows these steps:

1. MS i sets the transmit power to the maximum value P_{max} at the initial state.
2. MS i sends the data packet to its serving BS i using the transmit power $P_i(t)$ determined for time t.
3. On receiving the packet, BS i measures the SINR γ_i using (2.1) and calculates the current uplink rate $R_i(t)$ of MS i using (2.2).
4. MS i overhears the uplink rate information $R_j(t)$ of the adjacent MS j from the header information broadcast by its neighboring BSs $j \neq i$.

5. MS i calculates the next target rate $R_i(t+1)$ as

$$R_i(t+1)-R_i(t)=\frac{\lambda}{N}\sum_{j=1}^{N}\psi(|x_j-x_i|)(R_j(t)-R_i(t)) \tag{3.2}$$

which follows the same form as (3.1). The only difference is that the velocity of a bird v is replaced by the rate of an MS R. Here, we assume that $\psi(|x_j-x_i|)=1$ if the physical distance between BS j and MS i is less than the overhearing range r, i.e., $|x_j-x_i|\le r$. Otherwise, $\psi(|x_j-x_i|)=0$. If we choose $\lambda=1$, then (3.2) is revised as:

$$R_i(t+1)=\frac{1}{|N_i|}\sum_{j\in N_i}R_j(t), \tag{3.3}$$

where N_i is the set of neighboring BSs overheard by MS i and $|\cdot|$ is the cardinality of a set. Clearly, this is a distributed local-averaging algorithm for the uplink rates of the MSs.

6. If there is little difference between the next target rate $R_i(t+1)$ and the current rate $R_i(t)$ (i.e., $R_i(t+1)-R_i(t)<\varepsilon$, where $\varepsilon>0$ is sufficiently small), MS i maintains its previous transmit power.
7. Otherwise, MS i calculates its next transmit power $P_i(t+1)$ to achieve the next target rate $R_i(t+1)$ using the following relationship

$$R_i(t+1)=\log_2\left(1+\bar{\gamma}_i(t+1)\right)=\log_2\left(1+\frac{G_{ii}P_i(t+1)}{\sum_{j=1,j\neq i}^{N}G_{ij}P_j(t)+n_i}\right)=\log_2\left(1+\frac{\gamma_i(t)}{P_i(t)}\cdot P_i(t+1)\right), \tag{3.4}$$

where $\bar{\gamma}_i(t+1)$ is the estimated SINR of MS i to be used at time $t+1$. From (3.4), we can determine the next transmit power of MS i at time $t+1$, as follows.

$$P_i(t+1)=\min\left[P_{\max},\left(2^{R_i(t+1)}-1\right)\frac{P_i(t)}{\gamma_i(t)}\right]. \tag{3.5}$$

4. Results and Discussion

We consider a hexagonal multicell layout where the inter-site distance between adjacent BSs is 500 m and an MS is positioned randomly in each cell. The maximum transmit power, the path loss and fading models, and the noise figure are all based on the 3GPP evaluation methodology [4]. We also set the required SINR to 0 dB, which is generally used as the threshold to decode the received signal in cellular networks [5]. Monte Carlo simulations are performed 10,000 times using MATLAB. For comparison, we consider a scheme using the maximum equal power without power control and the SINR-based power-control algorithm with several target SINR values, in which each BS controls its transmission power in order to ensure that the received SINR satisfies a given target SINR [6].

Fig. 2 shows the rate and transmit power of each MS according to the number of iterations when the proposed power-control algorithm is used in a 7-cell topology. As the iterations proceed, all MS rates converge to the same value, and the maximum difference between the transmit powers of the MSs becomes uniformly bounded. Upon convergence, the MS that had the best rate initially (i.e., MS 7) uses the lowest transmit power, and the MS that had the worst rate initially (i.e., MS 6) maintains the maximum transmit power. In other words, MSs with good link quality reduce their transmit powers, while MSs with poor link quality maintain or slightly reduce their transmit powers in order to equalize the rates of all the MSs.

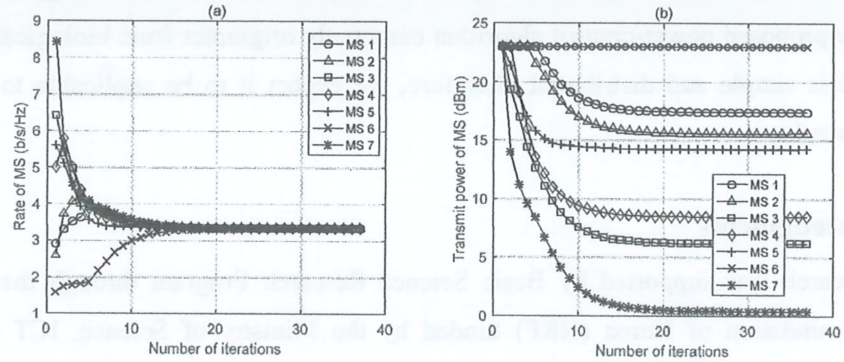

Fig. 2. (a) Rate of MS and (b) transmit power of MS vs. number of iterations.

Fig. 3 shows the average transmission power, outage probability, and energy efficiency of the MSs versus the number of cells. As the number of cells increases, the uplink inter-cell interference increases; therefore, the proposed power-control algorithm further reduces the transmission power in order to reduce the interference to the MSs. Therefore, the proposed scheme has lower power consumption than the other schemes. Moreover, the proposed algorithm shows a low outage probability. This implies that the proposed algorithm almost satisfies the target SINR in a manner adaptive to the change in the interference level, even though it uses significantly lower transmission power than the other schemes. Consequently, as the number of cells increases, the energy efficiency of the proposed scheme increases linearly, and it significantly outperforms the other schemes because it reduces the transmission power while maintaining a low outage probability.

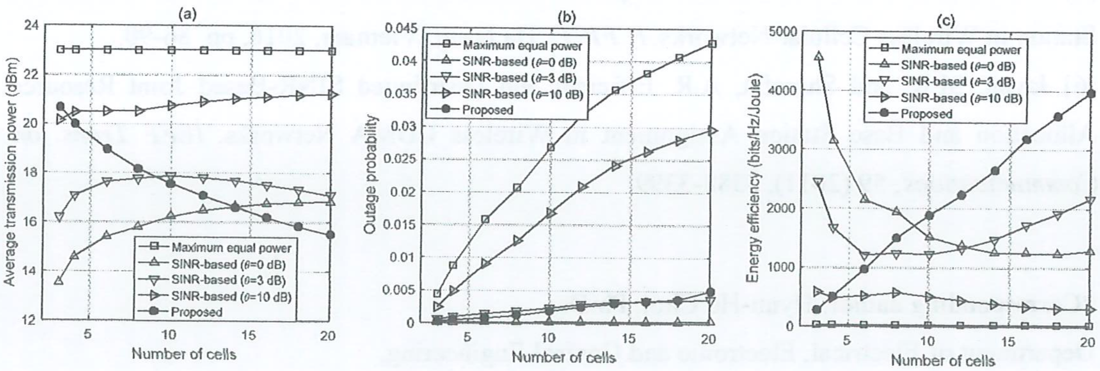

Fig. 3. (a) Average transmission power, (b) outage probability, and (c) energy efficiency vs. number of cells.

5. Conclusions

Inspired by the flocking behavior in which birds fly together in a group in an energy-efficient manner, we proposed a distributed uplink power-control algorithm in which each MS tries to match its rate to the average rate of the MSs in its adjacent cells by controlling its transmit power so that the rates of all MSs become equal. We verified that the proposed algorithm effectively reduces the power consumptions in the MSs, while maintaining a low outage probability, which leads to a significant improvement in the energy efficiency. Because the proposed power-control algorithm essentially originates from biological flocking behavior, it is simple and distributed; therefore, we expect it to be applicable to complex cellular networks.

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