REAL TIME SHAPING OF COVERAGE PATTERNS FOR WIRELESS COMMUNICATION WHEN BOTH TERMINAL AND BASE UNITS MOVE

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Abstract*: This paper extends recent developments in geographic load balancing techniques for cellular mobile communication systems using the Bubble Oscillation Algorithm (BOA), by investigating the added potential of simultaneously allowing the base stations to move. Enhancement of system capacity has been demonstrated in previous work by using the BOA to establish the optimal wireless radiation coverage shapes over a cellular network in real time and for both uplink and downlink in WCDMA networks. Cooperative coverage is advantageous, e.g. in the presence of hotspots. The ideal patterns generated by the algorithm can be used as the basis of synthesizing physical radiation patterns for semi-smart or fully adaptive antennas and for different wireless technologies. A procedure for finding the optimal location and direction of movement for a base station to minimize transmission energy is combined with the Bubble Algorithm optimization. A considerable transmission power reduction is observed from simulation results. A further simulation, where larger ships move to sustain near optimal wireless coverage of a set of smaller ships moving to a variety of different locations is used to give a visual illustration of the algorithm and make a comparison with a non adaptive approach.

Keywords: Geographic load balancing, bubble oscillation algorithm, antenna synthesis, mobile cellular network

1. INTRODUCTION AND BACKGROUND REVIEW

Non-uniform distribution of mobile handsets can present problems for resource allocation at base
stations (BS) [1] [2]. Many techniques have been developed to make use of limited radio frequency resource more effectively. Among the most commonly used are dynamic channel reallocation [3-5], cell splitting [9-12]. Apart from these allocation schemes focusing on radio frequency management, cell breathing [13] and dynamic cell shaping using semi-smart and adaptive antennas have been studied for several years [6-8], and cooperative shaping was initially developed in [22] [15].

Initial work on geographic load balancing used a cooperative negotiation mechanism into the determination of the subscriber list and hence the desired radiation pattern. The negotiation worked in a message sending-and-receiving style, asking adjacent cells for help when utilization in a cell exceeded a threshold [14]. Multiple simultaneous alternative requests were generated and sent to neighbouring cells, and the lowest price solution out of the responses offered by the neighbours when the time deadline is reached is selected. If no response is returned by the deadline then the coverage shape does not change. A neighbour can ask another neighbour for assistance in meeting a request, so a chain of requests could occur. The hop count is limited to two. In fact the message passing between base stations is notional, and simply reflects the structure of the algorithm. In practice the requests are method calls within an RNC, and distributed message passing would only be needed between RNCs for cells on an RNC boundary. A customized real-encoded genetic algorithm was developed to solve the global optimization problem and hence produce a benchmark for gauging the effectiveness of the real time negotiation [14].

Although the cooperative negotiation approach shows marked capacity enhancements for all antenna systems tested, its performance for fully adaptive systems, as distinct from semi-smart systems, caused some timing problems. The Bubble Oscillation Algorithm (BOA) was then devised and is described in detail in [16]. The BOA consistently produces results closer to the global solution than the negotiation based algorithm for all antenna models tested. The idea is based on emulating the way that a cluster of bubbles (c.f. base stations) equalize their pressures (c.f. traffic load). The algorithm has also proved to be more robust than the negotiation algorithm because less calculation is required. The BOA works in an iterative assign-oscillate-assign manner to find stable bubble contours for a whole set of bubbles. Each base station computes a utility of covering every MS up to its frontier. The latter is defined as the envelope of the maximum distance that the radiation of the BS could ever reach and still service a MS, for all possible shapes the antennas could generate. The utility of covering a MS is computed as a combination of a component related to the radial distance of the MS from the BS (this is called the repulsion force in figure 1 and this decreases with the distance from the BS) and a component which is related to the sum of the projections in the radial direction of all attraction forces from MS not presently assigned to any BS, i.e. the vacuums. The intuition is that if there are uncovered MS in approximately same radial direction as the MS under consideration, then this MS should have an increased utility, as covering it will help cover others. The utilities are used to sort the MS in preference order and assignment is performed using this order until the maximum capacity is reached. Some MS can be assigned to more than one BS and these are in soft handover. Assignment lists are iteratively updated in all cells, and this is the oscillation process. For reasons of space many details are not explained here, but e.g. for a fuller description of the application to WCDMA networks where power control is integrated into the process, see [19].

In fact there is still a form of negotiation in the BOA, but instead of explicit message passing it is implicit. The forces (utility adjustment) caused by the vacuums is what produces the cooperation between the cells. The cooperation is real but this does not imply that the intelligence needs to lie at the base stations or that the communication to support this cooperation is between the physical base stations. Most practical implementations of the Bubble Algorithm would have the decision making
centralized into RNCs.

Specific optimizations associated with the antenna technology, such as optimization of sector contours, can be formulated as optimizations that are computed after the assignment has been determined by the Bubble Algorithm. In principle the problem could be formulated as a combined optimization problem, but the advantage of fixing the assignment first and then overlaying the sector optimization is speed. For 3G networks this approach has been shown to produce very little apparent loss of capability [17][19].

The movement strategy superimposed on the BOA is simply aimed at optimizing overall power consumption for handsets in conjunction with the shaped radiation patterns of the cells. The movement strategy is described in section II, and the mobile network simulator used for performance estimation and the simulation results are discussed in section III. We also illustrate the potential of our movement strategy to track and maintain coverage in a wireless network where BS movement is also required in order to cover non-uniform traffic distributions. A simple ship landing story is included in Section IV.

2. MOVING BASE STATIONS TO OPTIMAL LOCATIONS

The Bubble Algorithm or the Cooperative Negotiation algorithm finds the ideal shaping for the wireless radiation patterns for the base stations in the network to maximize the operator’s utility and then the physical pattern is generated using the constraints of the chosen antenna technology. The algorithm can be viewed as a combined assignment and CAC algorithm that exploits the extra degrees of freedom from being able to change the radiation patterns cooperatively [15]. The location of the bases station is assumed to be fixed, as it commonly is.

If the base stations are allowed to move, another optimization problem can be overlaid on top of sector optimization algorithm (if used) and the Bubble algorithm. We assume that the base station is required to cover the terminal units selected by the Bubble Algorithm at that time and then compute an approximation to the ideal position of the base station given that it has to cover the mobile terminals chosen by the Bubble Algorithm. We assume the optimal position should be where overall minimum uplink transmission power (sum of transmission power of all the UEs that connected to a Node-B) can be achieved.

If we imagine that our base station can physically move very, very quickly we can iteratively apply the Bubble Algorithm, obtaining a new set of assignments and then apply the mechanism for estimating the optimal base station location conditionally on these assignments, until no further movement of the base station is suggested. We would expect now to have a good estimate of the optimal location of the base station allowing for the fact that a different assignment optimal could apply at the optimal location from which applies at the current location. This optimization process implies the capability to simulate the environment as predictions of received power at the mobile terminals from base stations at locations is needed. This may be viable in certain open environments.

The solution proposed here fineses these problems, by only suggesting directions for the base station to move, and then continually re-computing the movement directions to the base station position controller. In this case the true perceived power received by the mobile terminals can be used rather than that computed from a model of the environment. If an environment model is possible, such as for some air, sea and rural environments, then the predictive capability that comes from using the model can be incorporated into the approach suggested. Since what kind of vehicles can be used to install a moving BSs remains an open question transmission environment is uncertain only path loss is taken into consideration during our evaluation of power. Shadowing due to terrains is ignored and to
multi-path fading, RAKE receiver in CDMA technology can be used to counter the effect. Path loss model can be expressed as (1) regardless of radio wave frequency:

\[ P_{\text{trans}} = k \cdot d^\gamma \cdot P_{\text{recv}} \]  

where \( P_{\text{trans}} \) is the transmission power of a BS to a MS and \( P_{\text{recv}} \) the received power at the MS. \( d \) the distance from the BS to the MS. \( k \) and \( \gamma \) are propagation constants. \( 3 < \gamma < 4 \) is a typical assumption in urban propagation environment.

2.1. Computing the direction to move

Suppose that the base station in question is at location \((x, y)\) and that after the BOA has been run the n mobile terminals at locations \((x_1, y_1)\) to \((x_n, y_n)\) have been selected for coverage by this base station. The objective is to minimize the power used to service all n mobile terminals selected, i.e. to minimize

\[ P = \sum_{i=1}^{n} \left[ (x_i - x)^2 + (y_i - y)^2 \right]^\frac{\gamma}{2} \]  

(2)

Note that a simple uniform propagation loss of the form \( k'd^{-\gamma} \), where \( d \) is the distance from the base station and \( k' \) is a constant as in (1), is being used. We also assume perfect power control being used that guarantee power levels reaching BS from each subscribing MS equal and vice versa. The Bubble Algorithm, needs the true radial directions of the real locations, but then only needs the relative received powers at the terminal units. So the actual radial distance does not need to be differentiated from perceived distance. In the objective function the locations \((x_1, y_1)\) to \((x_n, y_n)\) are where the terminal units would be according to its perceived received power, if propagation loss actually obeyed the propagation model being used. Because of this the simple loss model can be a reasonable approximation to a variety of environments. Of course, they can also be assumed to be the locations as determined by, e.g. GPS, if we have confidence in the model. If we had a richer environmental model then the objective function would need to reflect this. If \( \gamma = 2 \) then the optimal solution is readily found as \( x = \bar{x} \) and \( y = \bar{y} \), where \((\bar{x}, \bar{y})\) is the centre of gravity of the (perceived) locations of the mobile terminals. If different bandwidths are used then the objective function can be modified to a weighted sum,

Usually \( \gamma > 2 \) so an exact solution is not available. However, the solution in such cases, may be not too far from the centre of gravity, so the centre of gravity can be taken as an initial estimate. Let \( x = \bar{x} + \varepsilon \) and \( y = \bar{y} + \eta \). Hopefully both \( \varepsilon \) and \( \eta \) will be small. The objective is to find an estimate for them. Computing \( \frac{\partial P}{\partial x} \) and \( \frac{\partial P}{\partial y} \) and putting to zero for a turning point leads to the simultaneous
equations \( f(\epsilon, \eta) = 0 \) and \( g(\epsilon, \eta) = 0 \) where:

\[
f(\epsilon, \eta) = \sum_{i=1}^{n} \varphi_i(\epsilon, \eta) \frac{\partial}{\partial \epsilon} (x_i - \bar{x} - \epsilon)
\]

\[
g(\epsilon, \eta) = \sum_{i=1}^{n} \varphi_i(\epsilon, \eta) \frac{\partial}{\partial \eta} (y_i - \bar{y} - \eta)
\]

and \( \varphi_i(\epsilon, \eta) \equiv (x_i - \bar{x} - \epsilon)^2 + (y_i - \bar{y} - \eta)^2 \).

Taking \( f(\epsilon, \eta) \) and using MacLaurin’s theorem and truncating second order and higher terms, namely using the approximation:

\[
f(\epsilon, \eta) = f(0,0) + \epsilon \frac{\partial f}{\partial \epsilon} \bigg|_{\epsilon=0} + \eta \frac{\partial f}{\partial \eta} \bigg|_{\eta=0}
\]

and performing a similar approximation for \( g(\epsilon, \eta) \) leads to two linear simultaneous equations with solutions \( \epsilon = \frac{A-D}{B-E} \) and \( \eta = \frac{1}{C} \{ -A - Be \} \) where the constants \( A, B, C, D \) and \( E \) are:

\[
C = -2 \left( \frac{\gamma}{2} - 1 \right) \sum_{i=1}^{n} \varphi_i(0,0) \frac{\partial}{\partial \epsilon} (x_i - \bar{x})(y_i - \bar{y}) ,
D = \sum_{i=1}^{n} \varphi_i(0,0) \frac{\partial}{\partial \eta} (y_i - \bar{y}) ,
A = \sum_{i=1}^{n} \varphi_i(0,0) \frac{\partial}{\partial \epsilon} (x_i - \bar{x}) ,
E = -\sum_{i=1}^{n} \varphi_i(0,0) \frac{\partial}{\partial \eta} \left\{ 1 + \frac{2(\gamma-1)(y_i - \bar{y})^2}{\varphi_i(0,0)} \right\}
\]

\[
B = -\sum_{i=1}^{n} \varphi_i(0,0) \frac{\partial}{\partial \epsilon} \left\{ 1 + \frac{2(\gamma-1)(x_i - \bar{x})^2}{\varphi_i(0,0)} \right\}
\]

Using the revised approximation as the new \((\bar{x}, \bar{y})\) (now without the interpretation of centre of gravity) gives a Newton-Raphson iterative approach. We also used Nelder-Mead Downhill Simplex Method which shows very similar results [18].

**2.2. When movement is constrained**

The optimization described above assumes that there is no constraint on the movement of the base station that prevents the stationary point from being the optimal solution. However, this is not necessarily so in general. In the example illustrate later, where ships are providing communications for landing craft, a constraint is that the larger ships are proscribed from coming within a certain distance from the shore. In this case the ships cannot move to the best place to provide maximal coverage of the craft, but must provide the best possible subject to the constraint, and the constraint is binding. The example illustrates application of a simple constraint. General constraints are more complex to manage. Here it has been assumed that all constraints are piecewise linear functions and the projected gradient approach, as described in, e.g. [19], is used. The basic approach is similar to the steepest descent gradient approach described above, but when a constraint is met in the direction of movement, the
direction is projected along the constraint boundary. In this way the solution remains within the feasible region.

3. EXPERIMENTS ON A CELLULAR NETWORK

Two experiments have been performed that integrate the application of the BOA with the location optimizer. The first experiment used an initial hexagonal tessellation and was designed to compute where the optimal base station locations should be, given the traffic demand at a particular time and evaluate how far the optimal location was from the centre of gravity as $\gamma$ increased from 2. Additionally each base station could not move further than half the cell radius, from its original location.

3.1. Network model for simulation

A 10×10 hexagon model CDMA network was used in the simulation with the following simplifying assumptions:

- Path loss is adequately modeled using the simple propagation model in equation (1)
- Perfect power control and guaranteed reception power level maintainable for all the MSs.
- Soft handover is not explicitly taken into consideration. (Though aspects are modelled.)
- Interference only has an impact on the capacity of a cell and is calculated as described in [21].

3.2. Simulation specifications

Our simulator works as a sequence of static simulations where the MS movements are computed from the underlying MS movement model and the BS movements from the base station movement models and the computed directions or optimal locations. The new locations are presented to the static simulator as a sequence of snapshots. In this experiment 100 snapshots of the network are used. Each snapshot represents the positions after an interval of 60 seconds. Initially the MSs are uniformly distributed and move randomly and the BSs are at the centre of the hexagons. To emulate the forming of unbalanced traffic, some of the mobiles gradually coalesce into hot-spots. More precisely, the network configuration is:

- There are totally 50,000 MSs within the network and all the traffic are always moving.
- 40 hotspots form during the simulation and each has a population of 1,250 subscribers so all the subscribers are within hotspots at the end. The relative location of each MS within a hotspot follows a normal distribution with a standard deviation of half the cell radius.
- A negative exponential call model is used for all the MSs and the average call time is 120 seconds and call inter-arrival time is 720 seconds.
- Maximum capacity of a cell is 120, approximately calculated according to an interference-based approach for CDMA network [21].
- Path loss constant $\gamma = 3.5$ and power level that reaches a BS from a MS is assumed to be 20 $mW$.

3.3. Simulation results

Simulation results are shown below (40 hotspots):
Fig. 2 compares system capacity. A moving BS network gives a greater capacity than a stationary BS network. Our simulations suggest that a moving BS network can perform better with respect to capacity when the size of hotspots is more localized. All the simulation results for a moving BS network have lower power consumption (Fig. 3). For a conventional network where coverage patterns are always circular, it has poorer capacity performance when there are many traffic hotspots. Although in Fig. 3 the conventional network shows the lowest power consumption performance, the low power is at the cost of a higher call blocking rate.

4. A MOVING NETWORK WHERE THERE IS A BINDING CONSTRAINT

4.1. A simple example: ships providing coverage for moving craft

This experiment was designed to illustrate better the potential of the approach and to demonstrate functioning of the algorithm when there is a binding constraint. However, no pretence at reality is claimed with respect to the application demonstrated. Three ships are providing communications supports to a large number of smaller craft, that are categorized into six types labelled A to F. Initially, all craft of type A are randomly located in an rectangular shaped region around the parent ships. Similarly for the other five craft. Craft of type A have destination in one part of the beach, type B another part and so on. Type is only used to indicate the destination. The goals of the different types of craft are such that their paths cross creating a temporary hot spot, before dispersing by type to their different destinations. The parent ships move to maximize the coverage of the craft. Each parent ship covers any type of craft. Initially the parent ships partition the coverage with the help of the BOA. The craft move at different speeds towards their destinations, and periodically the BOA is computed to find the current best coverage pattern, and the approximate optimal location for each parent ship is found, subject to any binding constraints. Initially the ships move closer together to provide better coverage of the hotspot area, but as the craft disperse, the ships also disperse, following the craft towards the shore. The ships have to stop following the craft towards the shore when the constraint is met, but can still cooperatively move parallel to the shore, to improve the overall coverage of the craft.

In this experiment real time assessment of the situation occurred every minute and at each of those times a “snapshot” of the (perceived) locations of the craft and ships is taken. It was assumed that the ships could move quickly enough to the desired optimal location, so that they were in their
desired optimal location, before the next assessment was made. (This by no means essential to the method described, just simply for convenience.) Also no predictive capability is assumed. The optimal positioning of ships and coverage patterns for a snapshot were computed and the ship moved to that position, rather than anticipating the movement of the craft until the next snapshot. So the forecast of a craft’s location in the next snapshot was simply its location in the current snapshot, which is clearly not optimal.

4.2. Simulation configuration

- A simulator similar to that used for the cellular network simulation is used, again with 100 snapshots and the same propagation loss model.
- The number of craft is 600; 100 for each type (A-F). The capacity of a ship is 200. Since three ships are given a capacity that is just enough to cover all the landing craft, to prevent coverage loss we need to keep making assignment and position optimization throughout the journey towards the shore.
- All craft are imagined to be communicating all the time.
- The coverage frontier of each parent ship is such that two ships are not enough.
- For comparison a simulation where the ships move in straight lines parallel to each other with circular coverage was also done.

4.3. Simulation results

Fig.4 shows three snapshots superimposed. From left to right: the snapshot shows the craft uniformly distributed in a rectangular region around the ships, initially; the next snapshot is the fiftieth one, where many craft are crossing each other and a large hot spot has been created; and the next is the final one, where ships are moving on their constraint boundary to optimize the coverage. Un-covered craft are indicated using black triangle. Here the shaped contour of each ship is a desired pattern. In this simple experiment the pattern has not been synthesized for antenna radiation actualization, and other physical constraints have been ignored. Such issues have been addressed in [15].

![Fig.4. Snapshots from the simulation](image1)

![Fig.5. Trajectories of parent ships](image2)

It can be seen from Fig.5 that the algorithm ensures that the ships indeed move in the correct directions, moving together and then apart as the craft disperse, and finally along the boundary. Fig.6 compares the coverage performance between parallel ship movement pattern with circular coverage and our traffic-tracking movement pattern with real time shaping. Enhancement is obvious. The
parallel pattern shows an advantage at the end because the craft are uniformly distributed along the shore by construction. This highlights a deficiency in the current algorithm as the optimization process is locked into optimizing for only those crafts it knows about. Modifications to the current algorithm are being made to resolve this.

![Parallel pattern showing advantage at the end](image)

**Fig.6. Number of un-covered craft**

5. CONCLUSIONS AND FUTURE WORK

A new method for finding optimal cooperative coverage of traffic units that can work for a variety of antenna and network technologies has been described. It builds upon previously described approaches for finding the best coverage shapes assuming the antennas are, in some known way adaptive. Currently the cooperative coverage of mobile terminals, using the technology of domestic MSs, such as WCDMA, from flying aircraft is being investigated. We are also developing the work on geographical load balancing in several other important directions. The first is to incorporate richer models of the world, by integrating the BOA with models of, e.g., urban environments, created by network planning tools. Secondly, the approach is ideally suited to providing differential QoS by giving different utilities to different requests, based on user criteria.

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