Space/Time Methods for Beamforming in Mobile Communications

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Abstract

We consider the application of beamforming techniques at the base stations of mobile communication systems. Three fundamental issues are addressed: aquisition of coherency information, mobile tracking and multipath handling. The paper presents two complementary approaches to the problem of coherency analysis: one based on an estimate of the correlation of all pairs of detected arrivals, the other using a learned model of the propagation environment. Mobile tracking is done by a multilayered neural structure, that is able to do the fusion of all available information (provided by one or both the coherency analysis methods), mantaining a map of the groups of coherent arrivals seen by the antenna. Finally, we show performance improvements that can be acieved when the tracking information is used to conveniently steer the reception antenna.

1 Introduction

In this paper we consider the aplication of beamforming methods at the base stations of mobile communication systems. The goal of applying beamforming techniques is to be able to achieve selectivity of the received signals based on their directions of arrival, i.e., to separate signals from distinct sources and thus be able to cancel interferences. With these systems, the antenna pattern is controlled on line, by electronically steering its beam towards the desired directions. To be able to define the antenna pattern, information about the mobiles directions is thus necessary. Once these are known, the beampattern can be defined using available algorithms, that correspond to different performance objectives: to cancel interferences incomng from a set of prespecified directions, to minimize signal estimation error, etc. In a mobile environment, another important impairement besides interferences has to be considered: the fact that a given mobile propagates trough a discrete set of paths to the receiving antenna, i.e., the existence of multipath propagation. Two extreme approaches to this problem consist in: (i) trying to cancel all the arrivals from a given mobile except one; (ii) trying to optimally combine all the arrivals, to improve signal to noise ratio. In between these two extreme approaches, one can try to separately receive each path, and to combine them in a temporal post-processing stage (here again, a number of possibilities exist: combination, selection of strongest, etc.). In any case, knowledge of the set of mobiles present and of the set of directions of arrival corresponding to each one is determinant to adequately control the antenna beampattern. In the paper, we present a structure that yields this information, to be used for beam steering and/or path combination.

The multipath structure as seen at the base station depends on the configuration of the cell (position of important reflectors, such as buildings) and on the antenna beampattern itself. This information changes from cell to cell, and even with atmospheric conditions. While a priori knowledge of the cell layout together with a realistic propagation model can be used to infer the dominant characteristics of the multipath structure, they can only hope to predict a nominal model that, in practice, will depart from true instantaneous operating conditions. In this paper, we propose a structure that adaptively learns this structure, allowing the association of several paths as possible reflections from the same source. Since this association structure may yield false associations between the detected rays, we process its output through a neural tracking mechanism, that keeps only those coherency groups that show temporal persistance. Besides the associations generated by the propagation model, the tracking mechanism uses also association information generated on the basis of the coherency matrix of the detected rays.

The paper is organised in the following way. The next section discusses the overall functional organization of the antenna front-end, identifying the blocks to be discussed in detail subsequently. In section 3 we propose two complementary mechanisms for coherency detection, discussing the interest of their combined utilisation. Section 4 presents the tracking mechanism, showing an example of its behavior. Receiver design is addressed in section 5, where the results of two distinct approaches are compared. Finally, section 6 concludes the paper.

Figure 1: Antenna front-end organisation.

Figure 2: Spatial Power Distribution.

Figure 3: association of rays using a spatial model.

2 Antenna Front-End

We present in this section the organization of an antenna front-end using an adaptively steered array, that can support multiple mobiles operating in the same frequency channel. In figure 1 we show the relevant modules of the front-end.

The *surveillance beamformer* is a fixed multibeam antenna, that gives indications of the rays present. In our simulations, we used a conventional delay-and-sum (D&S) beamformer. The spatial power spectrum distribution in the cell is estimated by computing the power at the outputs of each beam i of the D&S beamformer:

$$P_i = \frac{1}{K}\sum_{k=1}^{K} y_i(k) y_i^H(k)$$

where $y_i(k)$ is the (complex) sample of the output of beamfomer i at time instant k, K is the number of snapshots (time samples) used, and superscript ^{H} denotes the conjugate/transpose operation.

These power estimates are used to detect the directions of arrival (DOA's) present, by locating the maxima of P_i that exceed a given threshold (see Figure 2). This threshold can be determined on the basis of known expected power and noise level, to verify a given probability of detection.

The two blocks in a darker shade are responsible for providing mobile location (direction) information, grouping together detected paths corresponding to the same mobile, and are presented in detail in sections 3 and 4. The *receiving beamformer* has its beampattern defined by the weights generated by the module *beamweight computation*, according to the selected operation criterium (see discussion in section 5). Finally, when relevant, a *temporal post-processing* module may be used to combine multiple paths from the same mobile that have been isolated by the receiving beamformer.

3 Coherency analysis

As discussed in the paper introduction, we consider two complementary methods to aquire coherency information that allows the identification of groups of detected rays as arrivals form the same mobile.

One of the methods uses the following (instantaneous) estimate of the covariance matrix of the detected rays, designated here by coherency matrix:

$$\hat{S} = \frac{1}{K}\sum_{k=1}^{K} y(k) y^H(k)$$

where $y(k)$ denotes a vector that collects (at time k) the beamformer outputs for those beams where a ray has been deteced.

By observing the magnitudes of the off-diagonal entries of this matrix, we can define a partition of the set of detected DOA's, associating those arrivals that have large correlation values.

This method of association provides association information based only on the K most recent snapshots. It can, however, produce false associations, as well as split goups of multipath arrivals incoming from the same mobile (as we will see later, by the means of an example). It uses no *a priori* knowledge of the propagation characteristics of the cell.

The second association techique that we propose is based on an adaptively learned spatial (DOA) coherency model of the cell, implemented using a neural network. The rationale that motivates this structure is that the particular configuration of a given cell restricts the set of DOA's that can correspond to multipath arrivals from the same mobile. Figure 3 illustrates this mechanism.

Lack of space precludes the detailed presentation of this association mechanism here, and we refer the interested reader to [2]. We stress however, that it represents a fundamentally new approach to channel modelling in communications, not relying on a nominal propagation model resulting from (necessarilly approximated) knowledge of the cell geometry and physics, together with the use of ray tracing or alternative techniques, but rather on a distributed learned representation of the interesting features of the cell, from the point of view of ray association.

Note that the second association mechanism is based on a stored model of the cell, being, in that sense, complementary to the use of the coherency mechanism, that is based only on sensor information. The two should be used together, resulting on an association information that is compatible with both the received signals *and* aquired knowledge of the actual cell operating conditions.

4 Mobile Tracking

Either of the association meachanism described above can yield false associations of rays (specially in a dense environment), and suffers from *misses*, either due to rays that are not detected at the surveillance beamformer output, or to wrong partitions of the set of detected DOA's. To filter out false associations and to *fill in* the misses, a tracking mechanism is used, providing temporal continuity of the trajectories of the detected mobiles.

To track the present mobiles we use a layered neural Competitvely Inhibited Fuzzy Neural Network (CIFNN), which is a modification of the original CINN proposed in [3], suitable for target tracking of weak targets in cluttered noisy environements. This network maintains a filtered representation of the dynamics of the detected groups of DOA's, as generated by the association mechanisms.

The CIFNN possesses the clustering property already present in the original CINN net, meaning that it will cluster the state of its elements around the modes of the input data distribution. It is capable thus of performing adaptive estimation in a multi-object scenario, as it is the case of multiple traget tracking. CIFNN corresponds to the integration, at each node of CINN, of fuzzy information that gives the node membership as a descriptor of each detected object (target). Convenient manipulation of this fuzzy information allows track persistance in cluttered environements (close targets) and noisy observations. Robustness to false alarms relies on the clustering mechanism, while its ability to support undetected targets is explained by the network temporal dynamics. Again, detailed presentation of the equations governign network behavior is out of the scope of this paper, the interested reader being referred to [1].

Figure 4 displays the network organization. It keeps separate representations for distinct cardinalities of the set of grouped paths. Once a goup of P rays is presented at the net input, the corresponding subnet (N_P) is interrogated. If a good degree of correlation exists with a cluster, the input information is used to modify the state of the corresponding cluster of neurons in (N_p). Otherwise, subnet N_{P-1} is analysed, trying to match subgroups of $P-1$ rays in the input. If successfull matches are achieved, the corresponding clusters are updated with a low degree of confidence. Unmatched entries will try to find matches in subnets corresponding of smaller values of P, this process being repeated until the input is exhausted.

Figure 4: Tracking network organization.

Figure 5: Cell geometry.

We show in Figure 8 the output of the tracking network using association information provided by the coherency matrix for the following simulation scenario.

The cell considered covers a rotund, where is present a single inportant refelctor. The base station antenna is located at the center of the rotund, and has a circular geometry, whith elements equispaced at half wavelength at the carrier frequency. Each element is assumed to have a semi-hemispherical beampattern in the horizontal plane, and to cover uniformly the vertical plane. With this assumption, the secondary back direction lobe typical of this type of antennas is reduced.

As shown in Figure 5 there are four mobiles present, all operating in the same 1 GHz carrier, transmitting BPSK signals at 1Mbps. Mobiles A and B circle the rotund, while B and D are, respectively, leaving it and entering it. SNR's are 10 dB, the reflection coefficient in the building is 3 dB, power propagation losses varying with the reciprocal of distance.

Figure 6 presents in 3D space (z coordinate being time) the true pairs of DOA's corresponding to the mobiles trajectories.

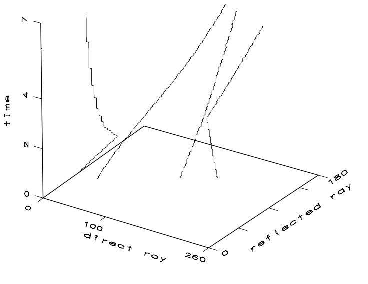


Figure 6: True DOAS's for Mobiles A-D.

In Figure 7 we display the associations generated using the coherency matrix. It is apparent from this plot a high probability of false associations, as well as a considerable probability of misses (isolated rays) during the period of analysis, specially when the true pairs of DOA's have (almost) common entries.

Finally, we show in Figure 8 the result of the tracking network, which shows that the network has been able to maintain a good internal representation of the present mobiles (their DOA's) during most of the period of analysis, even under the adverse input conditions.

5 Receiver Design

We consider here two distinct approaches to the problem of optimizing estimation of the signals emitted by the mobiles.

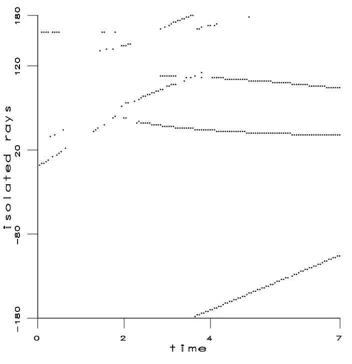
5.1 Recombination

This technique relies on time recombination of the signals belonging to each coherency group. The linear combination of the sinal replicas separately isolated by the receiving antenna is weighted by the reciprocals of the corresponding entries of the coherency matrix.

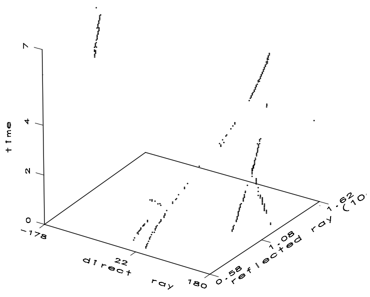
5.2 Interference Canceling

This alternative approach is based on the well known optimum (in the sense of maximizing SNR) beamforming methods. It differs from the previous one by using spatial instead of temporal recombination techniques. Knowledge of the position of the interfering mobiles and of the coherency matrix can be used to determine a structured estimate of the global interfering noise field (backgound noise plus all the other mobiles present), and consequently to specify the optimum SINR beamformer.

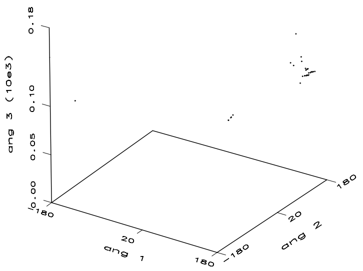
In Figure 9 we display the signal constellation for the scenario of the previous example as seen by an omnidirectional antenna.



(a)



(b)



(c)

Figure 7: Generated associations: *(a)* single rays; *(b)* pairs; *(c)* triplets.

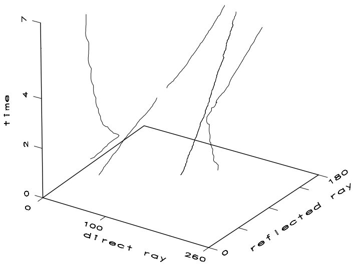


Figure 8: Resulting of tracking.

Figure 9: Received signal constellation.

The next two figures show the sinal constellations obtained using each of the alternative processing techniques previously described. In Figure 10 we show the signal constellation for one of the mobiles obtained using temporal combination. The two innermost clusters correspond to each ray received from the mobile, and the outer cluster is the result of their temporal combination. The improvement in SNR is apparent. The effect of an interfering ray can also been seen, leading to splitting of the middle cluster.

Finally Figure 11 shows the signal constellation for the second recombination method described (SINR beamformer). As expected, all interferences have been cancelled, leading to an almost perfect behavior.

Figure 10: Time recombination.

Figure 11: Spatial processing.

6 Conclusions

The paper described a front-end architecture capable of simultaneous operation of several mobiles in the same frequency channel. This study demonstrates the possibility of implementing spatial division techniques, that can considerably increase the capacity of mobiles communication systems. The problems of traget tracking and receiver design have been addressed, and examples of the achieved performances illustrated by means of simulations.

Acknowledgements

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[3] Michael Lemmon. *Competitively Inhibited Neural Networks for Adaptive Parameter Estimation.* Kluwer Academic Publ., 1991.